DOCTOR OF ENGINEERING (ENGD)

The Development of a Market Risk Profiling System Employing Behavioural and Emotional Finance Approaches

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The Development of a Market Risk Profiling System Employing Behavioural and Emotional Finance Approaches

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Acronyms Table

(CAPM) capital asset pricing model

(CRRA) coefficient of risk-aversion

(CRRS) coefficient of risk-seeking

(EEG) electroencephalogram

(EMH) efficient markets hypothesis

(fMRI) functional magnetic resonance imaging

(FRN) feedback-related negativity

(FRP) financial risk profiling

(FSA) financial Conduct Authority

(FSN) free scale network

(GSR) galvanic skin response

(HRV) heart rate variability

(IFAs) Independent financial advisers

(PANAS) positive and negative affect schedule

(PSM) problem structuring method

(RF) research framework

(SIS) susceptible-infected susceptible

(SMH) Somatic marker hypothesis

(VaR) value at Risk

(vmPFC) ventral medial prefrontal cortex

Thesis Abstract

This thesis employs a behavioural finance and emotional finance approach to analyzing the effect of investor biases and emotions on trading behaviour and performance. Furthermore, it incorporates a network approach to consideration of herding and emotional contagion across financial markets. The research is undertaken to advance both academic understanding and, in the spirit of the Engineering Doctorate (EngD), practical investment product development for the sponsoring organization (CheckRisk, see https://check-risk.com). This thesis reviews the relevant literature in behavioural finance, emotional finance and neuro-finance, and delves into the nature of networks, and of risk, risk-management and decision-making under various states of emotion and uncertainty. Building upon this literature review, our main experimental contributions to the field concern the development of a market risk-profiling system, based around behavioural questionnaires and a novel neuro-finance trading game. We tested our trading game on students, which provided a 'proof of concept' for the product. Next, we discuss how CheckRisk could market this risk-profiling product towards real-world traders and independent financial advisers (IFAs). Our research initially focuses on biases and emotions of individual traders, and then moves on from the 'micro' (individual traders) to the wider 'macro' (market-wide effects of emotional contagion across investors) areas of interest, particularly herding behaviours in financial markets. To explore these cascading phenomena, we employed network analysis and agent-based modelling. We suggest that this approach provides a basis for future academic and practitioner research, combining biases at the individual level (from the market risk-profiling system) with market-wide emotional contagion.

Background of the research program

Origins of the Engineering Doctorate (EngD) alongside other PhDs

The doctoral qualification, typically known as a PhD, has diversified in the UK since the 1990s, leading to alternative high-level degrees that are better suited to accommodate the needs of different professions such as medicine (MD), education and now engineering (EngD). These now sit alongside the traditional Doctor of Philosophy qualifications (PhDs).

The origins of the engineering doctorate lie in the 1990 Parnaby report, which concluded that such a qualification should be “distinct from, and complementary to, the traditional existing PhD”, which was at the time criticised for lacking relevance to the more practical needs of industry. Many industrial companies viewed traditional PhDs as necessary, but viewed the traditional PhD as too narrow and academic for industry's needs. It was also noted that standards were declining.

The report therefore recommended to the Science and Engineering Research Council, the UK research council that funded PhDs in engineering at the time, that a pilot doctoral programme “encompassing a broader range of training be established alongside the traditional PhD”. It was also recommended to contain the following components:

1. A significant, challenging and original engineering problem or set of problems undertaken as a partnership between industry and academia. This should be designed to give the candidate experience in team work, engineering project management (including financial aspects and working within prescribed time scales) in addition to in depth knowledge of an engineering problem.

2. Taught coursework (of high quality and assessable) to complement and enhance the experience of the individual in both technical and non-technical areas.”

It is worth noting at this point that the two factors above compliment the wider and traditional requirements of all PhDs. The Quality Assurance Agency for Higher Education (QAA), an independent body that holds up standards and quality on UK higher education, publishes a set of doctoral descriptors that are requirements for all doctoral qualifications, and students must demonstrate:

1. The creation and interpretation of new knowledge, through original research or other advanced scholarship, of a quality to satisfy peer review, extend the forefront of the discipline, and merit publication.

2. A systematic acquisition and understanding of a substantial body of knowledge, which is at the

forefront of an academic discipline or area of professional practice

3. The general ability to conceptualise, design and implement a project for the generation of new knowledge, applications or understanding at the forefront of the discipline, and to adjust the project design in the light of unforeseen problems.

4. A detailed understanding of applicable techniques for research and advanced academic enquiry.

Matching industry, university and government needs

Research-oriented universities integrate their research and teaching activities so they energise each other: teaching adds to the impact from the research, and quality research brings better subject matter for teaching. Universities can also work with their national research councils, and in this regard the relevant research council, the Engineering and Physical Sciences Research Council (EPSRC) worked with research-centric universities to found Industrial Doctorate Centres (IDCs) to foster better collaborations with industry in guiding and implementing EngDs. IDS grants are thus usually awarded to universities with a well-established and proven track record in research and have good relationships with industry.

The UK Government's needs are expressed through the research councils, which are broadly speaking, to increase the economic competitiveness of the UK on the global stage and to bring benefits to the country's people (note that EPSRC from April 2018 has become part of a single wider research council-like body, currently to be known as UK Research and Innovation). EPSRC (and later UKRI) monitor the IDCs so research and doctoral training are recorded according to current research council policy. EPSRC guidelines stress that the standard of academic or intellectual prowess for the EngD should be at least as high as for a PhD degree – that is a clear and original "contribution to knowledge" or similar).

The EngD normally takes four years to complete, and research engineer (RE) will typically spend 75% of their time working for a company on project work and 25% on university of other taught courses, which are usually at Bologna second cycle level and tailored to support the research.

The RE is most often an engineering graduate at the start of an engineering career, but the close links with industry mean that he or she can also be mid-career and seeking greater professional development. REs will be working towards an EngD in a multicultural environment with people containing a wide variety of skills, so communication, management and leadership skills are tested.

The majority of mid-career REs are employees, who may require a stronger business case because corporate costs can be significant, but in practice this often leads to highly motivated individuals keen to advance their careers with the professional EngD qualification. It is worth noting that the original remit of the Parnaby report encourages such a commercial orientation for increased impact of research in industry.

Networking and publishing towards an EngD

Learning with other EngD REs (peer-to-peer learning) is a crucial component of any educational experience. As work in the industry progresses, care should be taken for the EngD candidate to develop networks for learning outside of the organisation, from attending physical and virtual seminars and conferences for industry to university-based groups.

The life cycle of many industrial projects can be shorter than that for the four-year time-frame of the EngD, and project goals can sometimes be met without the necessary creation of formal, academic contributions to knowledge that are expected. Therefore, REs are encouraged to publish publishable papers on their work as they proceed, although Intellectual Property (IP) constraints in private companies may inhibit external peer review and subsequent open publication. In these instances, recorded internal peer review inside the company, which might contain seasoned professionals, can provide crucial and critical feedback for research endeavours. Such internal or private external reviews can demonstrate to examiners that the work is publishable and worthy of contributing to the EngD qualification.

The sponsoring company

CheckRisk (see www.check-risk.com) is a trusted provider of risk services to over $70bn of risk assets globally. The company provides consulting services, risk models to aid decision making, formulates risk strategies and risk management systems, and dispenses asset management advice. The company focus is primarily on answering whether clients are being paid to take the risk, and its stated aim is “to simplify the complexity of risk”.

The company uses algorithms and new theories to transform the way in which we can manage risk. The company brings together the latest forward-looking methods and translates them into an output that is easy to understand.

CheckRisk recognizes that there is no single ‘perfect’ approach and that there will always be a certain amount of irreducible uncertainty, so simulations and different techniques are used to provide robust analyses. Together, this offers the best chance of providing robust solutions to clients’ problems. The company also believes that the future lies in combining modelling power with practitioner experience. Working closely with clients, they are aiming to be successful in customising risk knowledge to provide specific client solutions.

Since the financial crisis of 2008, investors have increasingly understood the importance of the interconnectedness of the financial system. Therefore, CheckRisk monitors the criticality and sensitivity of institutions to the global financial system. This can be particularly useful for looking at systemic risk, counterparties, industries and client’s portfolio. They use a number of techniques that enable the client to see complex non-linear effects, including cascade modeling and causal networks. These are perfect for stress-testing, and give the clients deep insights into the real risks.

Chapter 1 Introduction and Research Methods

1.1. Thesis introduction

Our study will strive to tease out how emotions influence financial decision-making by examining both emotional- and rational-based approaches in a simulated trading game. We developed a new market risk-profiling system (CheckRisk), based around a new behaviour-based financial questionnaire. In light of recent economic volatility seen from 2008, we will be specifically assessing trading performance during booms and crashes.

When examining the reaction to the recent 2008 market crash it is interesting to note that emotions have been portrayed as an influential causal factor. This negative view of the influence of emotions on decision-making appears to be prevalent in financial theoretical models. However, as we will see, psychologists offer a contradictory account of the role emotions play in decision-making.

Neo-classical economics has eschewed the investigation of emotions in favour of portraying decision-makers as 'rational' and unbounded in terms of mental resources. Newer developments in behavioural economics and emotional finance have taken an interdisciplinary route, embedding theories and findings surrounding individual differences in decision-making from psychology with models of human behaviour developed within economics.

Our study will thus further the field of financial decision-making by examining the role of emotions, using contrasting economic and psychological approaches. Crucially, we will build upon Lo and colleagues findings (see reference 2002, 2005 in Chapter 2 Literature Review), countering their limitations and assuring their validity.

Furthermore, by combining psychologically driven measures of self-reported emotional states, physiological measurements of arousal and economic models of behaviour, this study assesses and combines neuropsychological approaches to emotions with more financially driven models.

Finally, our study went to the heart of the subject by examining trading performance during boom and bust market situations where four different stock market simulation tasks were performed. Each participant had to decide whether to invest or not in a stock during a ten-year period, and participants' attitude to risk as well as their explicit and autonomic implicit emotional arousal was assessed.

Our study measured implicit level one emotion through galvanic skin response (GSR), which is of considerable practical due to its great temporal resolution, which is essential for the investigation of real-time risk-processing and decision-making. Explicit level three emotions were measured using the positive and negative affect schedule (PANAS) self-report questionnaire that provides independent measures of positive and negative affective states. Finally, explicit level four emotions were assessed through a 'Financial risk-profiling questionnaire' measuring participants' risk and loss aversion.

When using questionnaire or surveys to assist clients, sound financial advice (when relying solely on the questions) can only be given if the questionnaire is soundly constructed and executed well. But wide variation has been found, such as Palma and Picard (2010), in how they elicit subjective risk tolerance, and objective measures of risk tolerance do better. This variation results in clients receiving a recommendation for a lower risk portfolio after taking one test, and being recommended a higher risk portfolio from another test.

Criticisms of questions in such tests centre on how they can reliably (and consistently) measure willingness to accept investment risk. Questions relevant to the field, but not directly relevant to investments (about hypothetical gambles risk-taking for example) can be a distraction. Investment knowledge and experience can be good predictors of the willingness to take risks. But analyses of individual questions suggest that the ability to moderate emotional responses (risk composure) and behavioural preferences like loss aversion can be very useful.

1.1.2 Thesis structure

This thesis is organised in the manner shown in Figure 1.1. Chapter 1 here introduces the research and purpose of this chapter is to provide the reader with information and context to be used throughout the remainder of the thesis. It attempts to highlight the complex nature of the problem and the pragmatic reality of needing a multi-disciplinary approach to addressing the research questions.

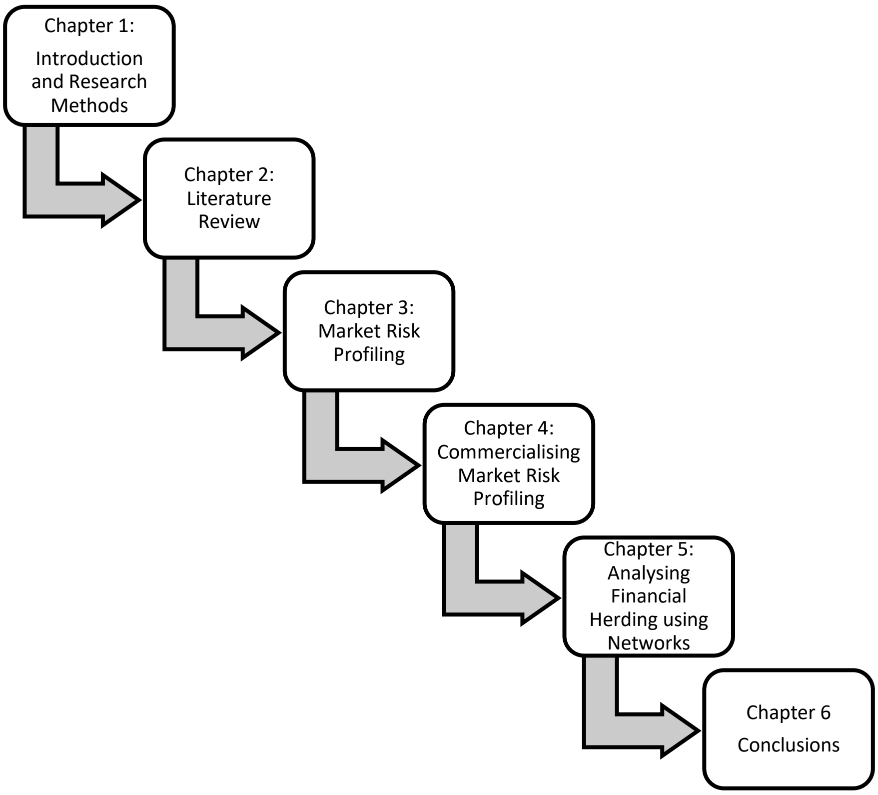


Figure 1.1 Thesis structure.

In Chapter 2, the literature review, reflects the field of study and contains materials from behavioural finance, emotional finance, network science – all quite decentralised fields with contributions from mathematics, physics, biology, sociology, psychology, computer science and likely much more.

We first (see 2.1 Introducing risk and risk management) briefly introduce the concept of risk which has been central to the theory and practice of finance since. We review how risk and risk management are defined in the academic literature, the need for risk management, and risk management has only emerged as a field of independent study in the past 20 years. We also discuss some of the quantitative techniques applied in the industry, and provide examples what happens after risk management failures and detail some causes. These are factors that determined the wider framework of the research work that follows.

Chapter 2 then moves on (see 2.2 Risk, emotions and decision making) to review literature on the influence of emotions on decision making, a core part of our experimental work as presented in Chapter 3, exploring newer fields such as neuroeconomics.

The literature review then moves on (see 2.3 Risk assessment, perception, aversion and tolerance) to matters that affect how people are affected by risk. This section is relevant to the development of our risk-profiling questionnaire as detailed in Chapter 4.

Finally, the literature review chapter (see 2.4 Herding and the topology and dynamics of networks) reviews papers and studies relevant to the herding modelling work presented in Chapter 5.
Chapter 3 presents the experiments, results and discussion around our simulated trading game as tested on 30 participants. This Chapter 3 contributes to the ongoing debate in behavioural finance and psychology regarding the efficacy of emotions in investors' financial decision-making. Are emotions good or bad for investors? The chapter provides an examination of the role of emotions in financial decision-making two contrasting approaches emerge: the emotion-as-bias inducer account endorsed by economic theories and the emotion-as-facilitator approach as theorised by psychological models. Results of such a dichotomous role of emotions were assessed in the context of overarching theoretical models. We also add to the existing information cascade and herding research by developing an emotional finance model that examines the effects of phantasy investors on the decisions of rational investors under dynamic pricing.

Chapter 4 is the product development part of the Eng Doc. We look at the commercialisation potential of the market risk-profiling questionnaire and we identify a rapid evaluation method, the 'Stage-Gate 3 Scorecard for Project Selection', and apply it to a risk-profiling system developed within Financial risk consultancy. It is concluded that the Stage-Gate 3 Scorecard is a promising approach for rapidly evaluating the commercial potential of emergent potential products. We also describe the CheckRisk Platform development and layout and it is potential.

In Chapter 5, we consider the effect of investor behavior and emotions on the market as a whole using network analysis, building on having considered individual investor biases in the trading game in the previous chapter. We have developed network emotional cascade and herding model using scale-free networks and showed how cascade and herding developes and evolve over four price paths, so in this chapter we go from micro-level to macro-level. This research and product development is part of CheckRisk: network analysis development model, where the sponsored company would like to develop early warning risk to detect herding and bubble formation.

Chapter 6 Conclusions the summarises and integrates all findings from the literature and experimental work previously described.

1.1.3 Introduction to research and research questions

This section describes the approaches and methods used to ask the right questions to achieve the research objectives and explains the assumptions made in addition to the choice of research approach and systems engineering methods.

As a novice researcher, I looked to Saunders et al.'s (2007) 'research onion' (see Figure 2) as a generic procedure by which to underpin the selection of appropriate research methods. The procedure prompts the researcher to consider their underlying assumptions to ensure suitable methods are used to increase the validity of their research[1].

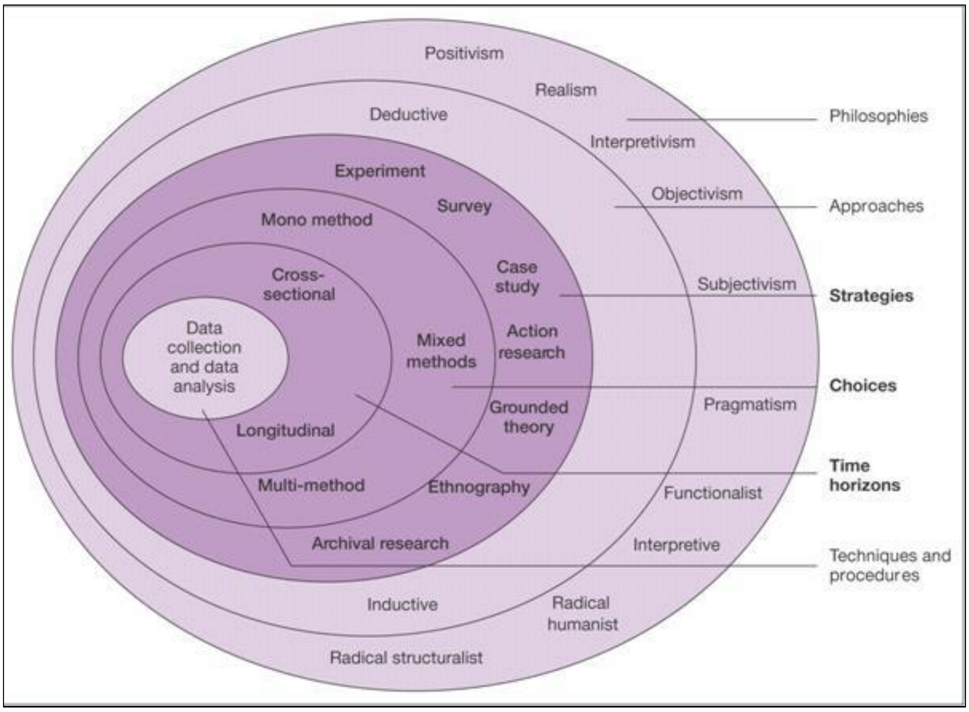


Figure 1.2 Research Onion (Saunders et al. 2007)

When defining the main research question, it is important to be able to capture the essence of all stakeholders' collective desires, whilst outlining the overall research direction. The following question captures the overall project in this respect.

[1] Research specifically refers to systematic and rigorous exploration aimed at answering questions or solving problems. It is about advancing knowledge through discovery and refinement. Saunders, M., Lewis, P. & Thornhill, A. (2006) *Research methods for business students*, 4th Edition. Harlow, Financial Times Prentice Hall.

How can adding behavioural and emotional factors into a market risk profiling system help in identifying individual risk tolerance; and how to aggregate this behavioural factor into network model to assess herding and emotional cascade at macro level?

This question is the fundamental purpose of this project but is also a very broad and ill-defined question. It necessary to explore the boundaries of the systems that were being studied and define them so they are fit for purpose.

The next section deals with providing a structured and rigorous approach to guiding the research in the exploration of both the problem and solution spaces. A Research Framework (RF) is adopted to guide the researcher's activities and the necessity for using a Problem Structuring Method (PSM) is established to effectively implement the work within an organisation and gain both the desired academic and business know-how.

Modelling is viewed as the process of building the model. In multidisciplinary models, this requires knowledge of both the behavioural finance theory and network models' bodies of knowledge.

The main research question is the overarching goal of this thesis. Due to the broad scope of the question, it has been broken down into several specific sub-questions, which can be answered more directly.

1.1.4 Research Framework

RF defines the activities required to provide a rigorous and structured research project. The ultimate aim of this RF has been to provide a systematic and systemic approach to the project that helped monitor the overall progress vis-à-vis to the main research question.

Firstly, a fundamental perspective of the project has been that the project will alter the researcher's worldview with every finding. This needs to acknowledged and addressed by the RF and a generic cyclical representation serves this purpose well.

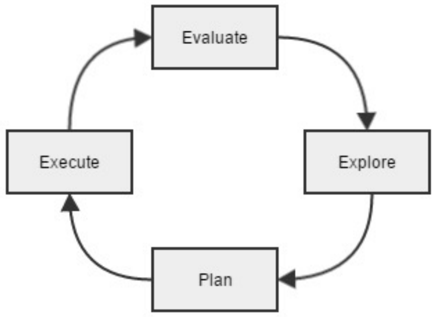


Figure 1.3 Cyclical generic PSM, a common variant of Shewhart's Plan-Do-Study-Act (PDSA cycle)

As is implied, this process/loop is time dependent and goes through several iterations through project conception to project end (Kemmis 1983). As such, whilst it provides a framework, it is felt that a time-dependent structure is needed to complement it to provide a pragmatic approach to the project and project planning. It is viewed that not only will the research cycle go through several iterations, but the main research question is broken into several sub-questions, which will be answered either explicitly or implicitly. This then provided a simple pragmatic RF to effectively plan the project – provided that the tasks can be broken down into tangible activities.

1.1.5 Research philosophy

The research philosophy assesses the researcher's epistemological and ontological views concerning the research to be conducted. As we did not study philosophy prior to starting the EngD, my philosophical stance concerning the nature of knowledge and reality is newly formed from only a handful of sources. As such, my stance is not with a specific philosophy, but within the antipositivist 'family' of philosophy.

In researching and developing the market risk profiling from a behavioural finance perspective, we do not believe that the *only* quantitative methods are appropriate for investigating human behaviour. The purely quantitative method fails to see human beings as actors who have an internal logic for their actions (Laing 1967). This is important because it is only through understanding this internal logic that any findings or meaning from the research can be gathered. To understand the internal logic, the researcher interprets meaning from the actors being studied. In doing this, the researcher is not an objective outsider observing the system (as assumed in positivism), but instead a part of the system being researched (Gill and Johnson 2002).

Evely et al. (2008) consider different philosophies to be along a positivist-subjectivist (another name for anti-positivist) continuum. We consider our research within the subjectivist half of this continuum but towards the centre rather than the far right. We disagree with the notion that 'action research'[2] is purely a solidly positivist research strategy. Action research involves continual reviewing and developing, and as such, means it sits in the middle of the inductive/deductive approach. A potential reason for the placement of action research firmly in the positivist paradigm might refer to the early American action research from 1920 to 1950 which was considered positivist, rather than the resurgence of action research in the 1970s as British action research (Wilfred Carr 2006).

1.1.6 Research approach

The research approach indicates the 'logic' of the research process and can either be deductive or inductive (Maylor and Blackmon 2005). The deduction is when the researcher uses general theories to hypothesise about more specific instances upon which the theories are then confirmed or falsified. Induction is where specific instances are investigated to create hypotheses that then evolve into theories (see Figures 1.4 and 1.5).

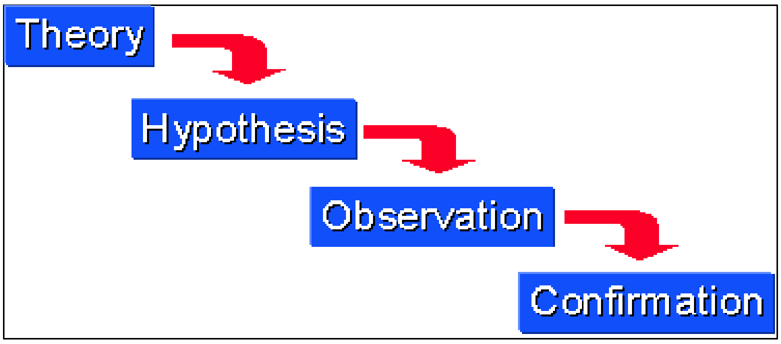


Figure 1.4 Deductive Research Logic (Trochim 2006)

[2] Lewin first used the term in 1946: "Given certain conditions a problem structuring approach *is* action research, not just a strategy for answering a research question. This has implications for the way in which the research is conducted, especially what constitutes data, and how the research is written up (rhetorical assumption)"

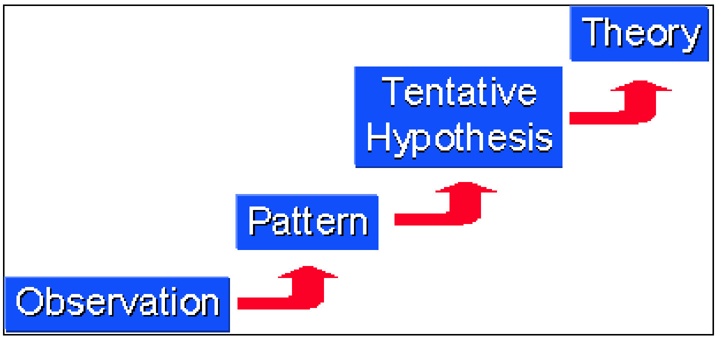


Figure 1.5 Inductive Research Logic (Trochim 2006)

The deductive research logic (Figure 1.4) tends to be associated with positivist philosophies, and the inductive research logic (Figure 1.5) tends to be associated with anti-positivist philosophies. The general associations of the different logics with the different philosophies is mainly due to generalisability and causal relationships. With deductive logic, over-arching theories are implemented in specific circumstances to test their generalisability. In order to hypothesise that the theory is appropriate for the circumstance, predictions are made based on causal relationships. When behavioural phenomena are being studied, as with this research, the deductive approach is inappropriate, because human beings do not behave in the predictable way necessary for causal relationships (Mead, 1934), and so generalisability is less important. As a result, we shall be looking into research strategies that use inductive logic, which emphasise theory grounded in empirical observations, and explanation based on an understanding of the 'real world'.

Inductive logic has been criticised for its lack of structure and because it is not replicable and bias cannot be ruled out (Gill and Johnson 2005). These criticisms are based on the difficulty in assessing research undertaken using inductive logic with deductive logic criteria for quality, and as such, different criteria should be used. The goal of research undertaken using inductive logic is producing valuable and transferable results (O'Leary 2004), which can be through using intuitive analysis in the unique situation to produce original results (Maylor and Blackmon 2005). What is important is being able to transfer understanding to other similar situations, not replicating the results accurately.

This research is being conducted within a market risk consultancy firm, so the transferable understanding will be to world wide consultancy projects undertaken by CheckRisk. Other consultancy firms can potentially benefit through the dissemination of this work through journal papers, conferences, as other forms of knowledge dissemination.

Bias is related to subjectivity, and as earlier stated in the research philosophy, all human beings are subjective so subjectivity cannot be ruled out completely. Experimenter bias has even been shown in positivist experiments concerning rats and mazes (Rosenthal and Fode 1963). By working to an anti-positivist philosophy, subjectivity is not removed but instead managed. Two ways of managing bias are through neutrality where strategies to ensure unrecognised bias are removed (e.g. unbiased language in questionnaires), and through transparency where any subjectivity is acknowledged and discussed (O'Leary 2004).

Another issue surrounding inductive logic is the validity of the data gathered, and the quality of the raw data itself. With deductive research logic, validity lies with the use of correct variables, metrics, accuracy, and enough samples to make the findings statistically significant. With inductive research logic, there is less of a consensus on the validity of the findings, so much so that even the word 'validity' is scrutinised (Corbin and Strauss 2008).
Corbin and Strauss (2008) believe 'validity' to be too embedded in the positivist philosophy to be appropriate for qualitative data. Instead, they use the word 'credibility' (citing Glaser and Strauss, 1967; Lincoln and Guba, 1985) to indicate that the findings are believable and trustworthy accounts of the participants and the researchers, and that each research method will require its own judgement criteria in this regard.

1.1.7 Research Strategy

There are many schools of thought on different research strategies and many instances where different strategies overlap e.g. grounded theory ethnography by Charmaz (2006, p21-25); how case analysis and grounded theory can work together (Strauss and Corbin 2008 p325); how case studies are not research strategies as such, but a research design that uses different strategies (Maylor and Blackmon 2005).

There are two main phases to this research. The first, 'problem exploration', explored the current context for addressing the management of risk and behavioural finance. The second, 'action', described the development of market risk profiling. Our research strategy has been to implement different research methods under the umbrella of creating theory grounded within the data, influenced by constructivist grounded theory (Charmaz 2006). Through the lens of grounding the theory in the data we collect, we have implemented other research sub-strategies to fit with the aim of the phase.

1.1.8 Grounded theory

Grounded theorists base theory in the data rather than deducing testable hypotheses from existing theories (Charmaz 2006). 'The discovery of grounded theory' (Glaser and Strauss 1967) is the seminal work on grounded theory and was the start of a new era in research methodology, where the authors attempted to formalise qualitative analysis in all fields by proposing systematic strategies for practice.

The main aspect was the simultaneous analysis and gathering of data through codes, categories, and memo-writing (see Figure 1.6). By undertaking these processes simultaneously, the theory is developed at each stage of collection and analysis. Other aspects involve sampling data for theory construction rather than population representativeness and that the literature review should be conducted after the independent analysis to guide the critique and comparison of previous work to the newly grounded theory.

Today, there are many different sub-genres of grounded theory (Dey 1999) and it is considered that the methods used be flexible to ensure appropriate insight into the data (Strauss and Corbin 2008; Charmaz 2006).

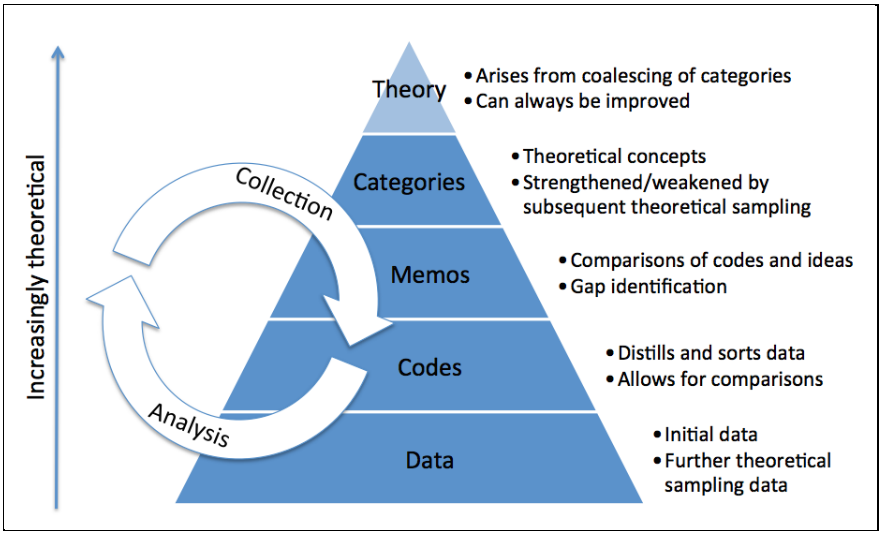


Figure 1.6 Overview of Grounded Theory (influenced by Charmaz 2006)

Charmaz (2006, p130) defined two main camps for grounded theory; constructivist and objectivist.

Objectivist Grounded Theory	**Constructivist Grounded Theory**
Positivist tradition	Interpretative Tradition
Data gathered is real	Data gathered is based on relationships and shared experiences of researcher with participants
Researcher is an objective conduit for research process to 'discover' a grounded theory	Researcher is a subjective participant within the research process and a creator of the theory as it is an interpretation
The 'how' is not considered	How participants construct meaning (and then possibly move on to why they are constructing meaning through looking at context)

Table 1.2. Differences between Objectivist Grounded Theory and Constructivist Grounded Theory (Charmaz 2006)

Charmaz (2006) emphasises the subjective nature of the researcher and how all grounded theories are interpretations based on the researcher context. In response to constructivist grounded theory, Corbin and Strauss (2008) argue the point of 'knowledge creation'. If the theories developed from constructivist grounded theory are still only interpretations in a certain context by a certain person, then are those findings actually useful in the real world? What was the point of the research if no practical outcome can be made of it? Corbin's pragmatism influences her opinion that a degree of conceptual language must be present to make use of the findings, as without it there is "no basis for discussion, conflict, negotiation or the development of a knowledge-based practice".

Our stance is affected by our purpose within this research context. We aim to add better understanding to the financial risk industry. Whilst conducting this research we have been a constructivist, understanding that our theories are an interpretation of my five years working on this subject. They are also affected through new findings in our day-to-day life as a research engineer, and although our findings are my interpretation they are as valid as an expert opinion.

1.1.9 Action research as influenced by constructivist grounded theory

For the 'problem exploration' phase we formed concepts and tentative hypotheses, and so constructivist grounded theory fit well. For the 'action' phase, we developed the options appraisal approach using action research as influenced by constructivist grounded theory.

Action research involves cyclical testing and analysing of feedback, similar to the cyclical collection and analysis of data with constructivist grounded theory. Feedback was also used to ground the requirements, improvements, and development of the approach within the data collected. The main difference is that action research is participatory through the action taken, rather than being passive as with constructivist grounded theory (B. Dick 2010).

1.1.10 Choices, time horizons, and techniques

We have used a multi-method approach over different time horizons. By using a variety of methods, we tailored the approach to suit the different stages of this four-year research project depending on the purpose of that stage, our findings, and the level of detail appropriate (Maylor and Blackmon 2008).

The problem exploration phase investigated the current academic and practitioner viewpoint of financial market risk and how it is managed in both a quantitative and behavioural finance way. Using different methods will help to triangulate our data and strengthen the concepts and tentative theories (Maylor and Blackmon 2008). Silverman (2001) states that triangulation should be conducted with caution as that the context of the data may be forgotten if the data do not support each other, which was noted during analysis.

The action phase involved cyclic testing and evaluating of data. The validity of the feedback gathered was addressed in a similar way to the problem exploration phase. The validity of the development of the approach using that data was achieved through self-critique, transparency, and a full explanation of our decisions and actions.

Table 2. Some of the many different philosophies that underpin social research, presented along a positivist–subjectivist continuum. The table demonstrates how the philosophies influence research strategies and methodologies, etc. (based on Crockett 1950, Brandt 1957, Feyerabend 1962, 1981a, 1981b, Husserl 1962, 1965, Marcuse 1965, Ricoeur 1978a, 1978b, 1978c, Sneed 1982, Burgess 1983, Brown 1987, 1998, Bourdieu 1991, Eger 1993, 1997, Yeung 1997, Moran 2000, Hellman 2001, Chakravartty 2004, Mayer 2006, and on extensive discussion with 12 researchers from different social science backgrounds at Aberdeen and Aberystwyth University).

	Positivist Approaches to Social Science				Subjectivist approaches to Social Science		
Philosophy	Extreme Positivism	Structural Realism	Critical Realism	Transcendental Realism	Hermeneutics	Nominalism	Extreme Subjectivism
Core Ontological Assumption	Reality as a concrete structure	Reality as a concrete process	Reality as an interplay between a concrete structure and influenced by perception	Reality is both a projection of human imagination and a concrete structure.	Reality as a social construction	Reality as a realm of symbolic exchange	Reality as a projection of human imagination
Methodological Criteria	External Validity, Researcher led, Quantitative, Empirical	External and Internal Validity, Researcher/participant led, Quantitative and Qualitative, Empirical	External and Internal Validity, Researcher/participant led, Quantitative and Qualitative, Theoretical and empirical	External and Internal Validity, Researcher/participant led, Quantitative and Qualitative, Theoretical and empirical	Internal Validity, Participant led, Qualitative, Theoretical and empirical	Internal Validity, Participant led, Qualitative and Quantitative, Theoretical and empirical	Internal Validity, Participant led, Qualitative, Theoretical and empirical
Types of Questions	Demographic and project related	Demographic and project related to structure of reality	Demographic and project related, acknowledging human perception of reality	Demographic and project related to human understanding of reality	Study of participant behavior	Participant response related to understanding of words	Participant response related to project
Research Strategy	Experiments, Surveys, Action research, Case studies	Ethnography, Case studies, Grounded theory	Survey Ethnography, Case studies, Grounded theory	Experiments, Ethnography, Case studies, Grounded theory	Documents, Speeches, Stories, Ceremonies, Advertising,	Ethnography, Case studies, Grounded theory	Ethnography, Case studies, Grounded theory
Method of data collection	Questionnaires, observation	Interactive interviews, Questionnaires	Interactive interviews, Questionnaires, which may use qualitative questions	Interactive interviews, Questionnaires	Structural semiotics, Discourse analysis, Psychoanalytic criticism, Interviewing, Ethnographic techniques	Interviews, Participant observation	Interviews, participant observation
Type of Analysis	Statistical methods	Statistical methods	Statistical methods	Statistical methods, Inferential statistical analysis phenomenological analysis	Dialectical process involving three "moments:": Social historical analysis, Formal analysis, Interpretation– Reinterpretation	Content analysis, Thematic analysis, Discourse analysis, Interpretive phenomenological analysis	Content analysis, Thematic analysis, Discourse analysis, Interpretive phenomenological analysis
Potential Interpretation	Generalization, inductive and deductively valid arguments Hypothetico-deducto mode	Generalization, although does not allow contingent generalizations to be treated as necessary causal mechanism, Hypothetico-deducto mode	Abstraction and retroduction, Generalization, although does not allow contingent generalizations to be treated as necessary causal mechanisms. Hypothetico-deducto mode	Process of retroduction, a posteri reasoning, use of analogies, Generalization, although does not allow contingent generalizations to be treated as necessary causal mechanisms	No Generalization	No Generalization as there can be no universal truth	No Generalization

Figure 1.7 Continuum of philosophical perspectives (Evely et al 2008)

1.2 Systems engineering perspective introduction

In the pursuit of making product development more effective, such as our risk-profiling tool CheckRisk, any improvement can be thought of as an innovation. Innovation can be classified into one of two broad classifications according to Utterback (1975, 1994): product and process innovations. Product innovation can be thought of as either a radical innovation (i.e. shifting the product paradigm – e.g. from propeller to jet engines) or an incremental innovation improving the product (i.e. variant designs – e.g. turbojet, propjet). However, it is process innovation that makes products more affordable and accessible to the general population by improving how products are developed. Given that repetitive designs form the vast majority of a product's development effort (K. Wallace, 2007) across all engineering disciplines, the economic value of process innovation cannot be overstated.

Process innovation can come in many forms: modelling (fidelity, computational power, efficiency, model simplicity), design-decisions (set-concurrent design, organisational setup), Manufacturing (Lean, Six sigma), and project management (enabling gate-keepers, management quality, adequate resource allocation, resource accessibility, critical-path analysis, PERT).

Engineering is the act of applying scientific knowledge in the pursuit of creating an engineered artefact. Engineers use the knowledge that has been developed theoretically, semi-empirically, or empirically to situations that have been analysed and constructed into identifiable problems in order to achieve a grounded solution. This is done by various models, which can be thought of as a proxy for how a system behaves.

However, models need to be constructed and then used. These both have great implication as to what level of fidelity and complexity is fit-for-purpose in a model. This section focuses on the building and the use of models. As in the endeavour of engineering an artefact, the model, modelling, and use of the model are a matter of trade-off. The best solution is thus not to the model with the highest fidelity, but to create a model that optimises the wider product development in the trade-off between the model and building/use of the model (Kossiakoff, 2011).

The more complex the product that is being modelled is, the more variables are needed, which usually requires more people (Maurer, 2007). This renders the modelling endeavour more complex, one that cannot ever be fully understood, even when analysing a product development process in hindsight. Therefore, in prediction, the problem can be thought of as "messy" (Ackoff,1979).

1.2.2 Research Questions

This section attempts to contribute to the overall research question:

> *How can by adding behavioural and emotional factors into market risk profiling system help in identifying individual risk tolerance; and how to aggregate*

behavioural factors into network model to assess herding and emotional cascade at the macro level?

From many research iterations, the following research and sub-research questions emerge and are answered in the following chapters:

- *Can social network analysis be used to circumvent financial market herding and complexity?*
- *Can herding and emotional cascade be used to construct a context driven series of networks?*
- *Can social network analysis be used to draw attention to real and emergent aspects of a system with a view to consolidating worldviews regarding needed interventions by regulators?*
- *Can network dynamics provide benefit as:*
    - *a) an analytical model that is able to consistently replicate real world phenomena in real-time?*
    - *b) a systems thinking model to draw attention to obvious, emergent, complex, and predictive properties?*

1.2.3 Proposed Approach

As was stated above, this thesis focuses on improving the modelling and use of market risk profiling. In order to improve this, it is necessary to analyse the purpose of modelling. Modelling can be thought of as a proxy representation of a given system. Epstein (2008) examines this subject and provides seventeen reasons to build a model. These are given as: predict; explain; guide data collection; illuminate core dynamics; suggest dynamical analogies; discover new questions; promote a scientific habit of mind; Bound (bracket) outcomes to plausible ranges; illuminate core uncertainties; offer crisis options in near-real time; demonstrate trade-offs / suggest efficiencies; challenge the robustness of prevailing theory through perturbations; expose prevailing wisdom as incompatible with available data; train practitioners; discipline the policy dialogue; 3ducate the general public; reveal the apparently simple (complex) to be complex (simple).

With reference to the work presented in this thesis, for instance, in Chapter 5 we use a model to guide to the experimental design and data collection, illuminate core dynamics, discover new questions, and reveal the apparently simple to be complex. Using this to understand how and why the model is used, provides the purpose of the model, and criteria around which to optimise.

1.2.4 System boundaries

Maurer (2007) provides a very useful framework (see Figure 1.8) where the research draws attention to the interdependence of the market, product, organisational and process complexities.

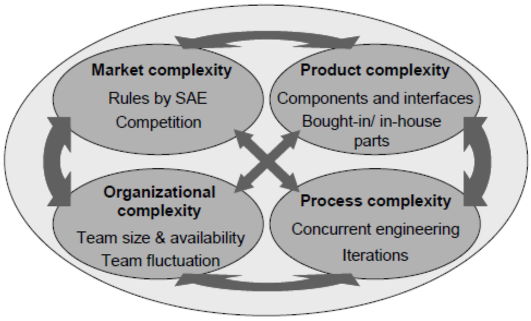


Figure 1.8 Complexity in Product Development from Maurer (2007)

It is this view that is adopted when considering the product development enterprise, such as the CheckRisk presented later in Chapter 4. It is assumed that any changes in the model need to account for significant effects or affects from/to the adopted enterprise view. The system is complex, and a conceptual model that shows emergent behaviour is needed to provide decision-makers with more information, foster alternative worldviews, and provide an understandable model that can be used to debate in clear and common ways.

In terms of our problem-solving methodology, the greatest challenge in analysing rework requirements and volatility is understanding why it occurs. This requires understanding how, what, where, when and how much it occurs. In simple cases, this can be trivial. However, as has been established, intervening in the process are organisational complexities, which are embedded in a network of people, can be a messy problem because it is impossible to understand exactly how people will react and interact.

Thus, to be able to optimise modelling, it is necessary to develop a framework that provides the know-how, know-why, know-what, know-when, and know-how pertaining to problem/opportunity-situations in complex systems.

Inevitably, the more complicated a system is, the longer, more expensive, greater requirement for resources and more changes to the routine and operation is guaranteed. There are two possible approaches to dealing with this complexity when adopting a black-box view. The first is adopting a solution framework, which accepts the complexity and attempts to optimise the system through a series of improvements, which will yield an emergent improvement.

The alternative requires understanding complexity and managing the complex systems to yield the desired improvement. Complexity has been studied in great depth in many different fields. However, in Systems Engineering, it is typically authors in Soft Operations Research that provide the basis for complexity management.PSMs are at the forefront of complexity management and utilises stakeholders' worldviews to take a pluralist perspective on any problem.

1.2.5 Research method ethics

The general definition of ethics research "The value of intellectual integrity grounded in the practice of research as the activity of an academic community. It encapsulates the idea that research is a shared and objective search for truth, not distorted by special interests. It means, in particular, that research might not be undertaken if it is funded by bodies which are looking for preconceived conclusions and liable to bias the investigation. It means also that the results of research should normally be made publicly available to the wider academic community, and should not be the private property of the funding body."

It was stated that the ethical code and frameworks are not well developed in all research areas, for example in the business and management systems. Given the importance of ethics for the conduct of research, it should come as no surprise that many different professional associations, government agencies, and universities have adopted specific codes, rules, and policies relating to research ethics. The following is a rough and general summary of some ethical principles that various codes address: honesty; objectivity; integrity; carefulness; openness; respect for Intellectual Property; confidentiality; responsible publication; responsible mentoring; respect for colleagues; social responsibility; non-discrimination; competence; and legality.

The ethics of financial and banking profession became a very important topic following the financial crisis of 2008. Questions were raised by the public and the media about the unethical behaviour of some of the mortgage lenders and investment banks who facilitate complex financial instruments i.e. Credit Default Swaps (CDS), and the marketing of them to investors without highlighting the risk involved. Ethics in the financial services industry affect everyone, even costumes because even if you are not financial services professional, you're a consumer of financial services products.

Often the aims and objectives of shareholders are not the same as the stakeholder and they come into conflict in some instances. The conflict often arises as while shareholders want short-term profit, the other stakeholders' desires tend to cost money and reduce profits. The owners often have to balance their own wishes against those of the other stakeholders or risk losing their ability to generate future profits (e.g. the workers may go on strike or the customers refuse to buy the company's product).

Common excuses for unethical behaviour in the financial and banking sector are "everybody else was doing it", "It's not that big of deal", "It's illegal, nobody will know." Regulators should play a greater role in improving standards and introduce comprehensive laws that every firm and individual have to follow or else risk penalty. Although codes, policies and principals are very important and useful, like any set of rules, they do not cover every situation. In reality, they often conflict and they require considerable interpretation which can be quite subjective.

It is, therefore, important for researchers to learn how to interpret, assess, and apply various research rules and how to make decisions and to act in various situations. The vast majority of decisions involve the straightforward application of ethical behaviour. It is in our human nature to incorporate and assess behavioural ethics when making decisions, however, it can be seen in some financial markets that these decisions can become impaired when the lure of profit is too much.

1.2.6 Financial systems visualisations and boundary exploration

The idea of using drawings or pictures is common to several problem solving or system thinking methods: "Systems thinking is a discipline for seeing wholes. It is a framework for seeing interrelationships rather than things, for seeing patterns of change rather than static snapshots. systems thinking is a discipline for seeing the 'structures' that underlie complex situations, and for discerning high and low leverage change" (Senge, P. M. 1990).
Visual diagrams are an important tool to explore a situation, identify system dynamics, represent stakeholder's needs, and representing a process. We live in a very literal world and we communicate

with each other in lots of different ways, although most of our (overt) communication uses either written ideas or spoken word.

Visualisation is a very different form of communication that allows us to think in new ways and encourage us to approach problems differently. Diagrams can be used to talk about complicated ideas and situations, and help to communicate ideas, but they are also useful for exploring areas we wouldn't normally be able to think about. Figure 1.9 shows a financial network system diagram where for over two decades central bankers and monetary/financial academics have had no incentives to study the financial system in an integrated way.

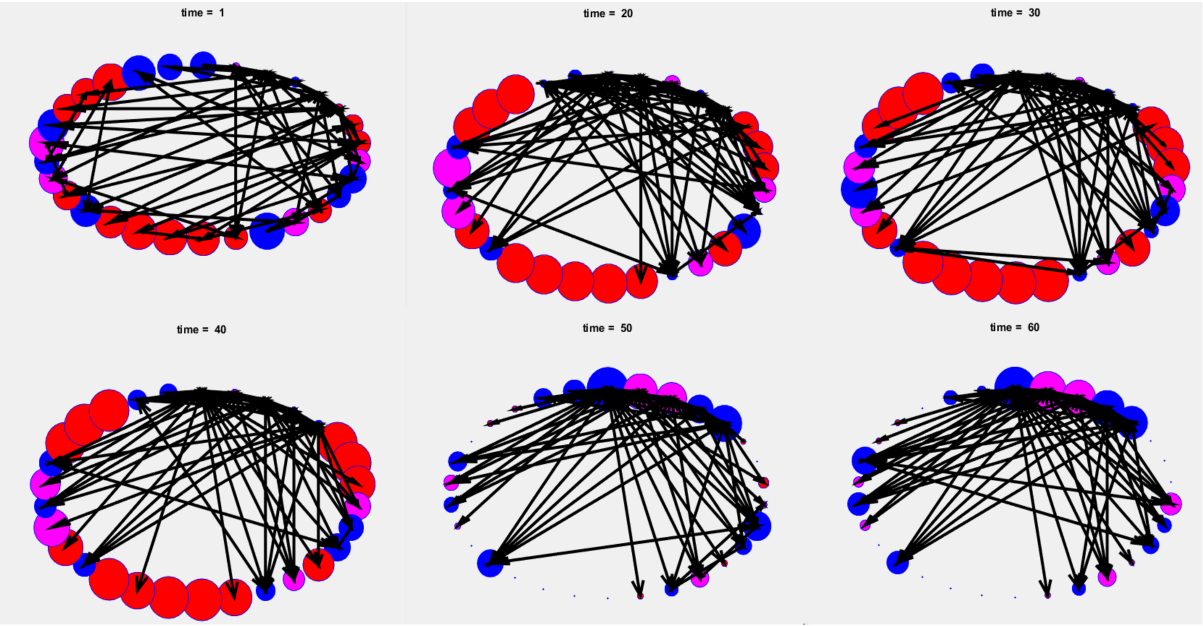


Figure 1.9 Network Herding Visualisation where nodes represent market participants and arrows represent participant's links

Rich pictures (Checkland, Peter B. 2000) are drawn at the pre-analysis stage *before* we know clearly which parts of the situation should best be regarded as process and which as the structure and it is very useful in exploring the situation. Exploring the problem by identifying stakeholders, dealing with worldviews, working closely with my industrial supervisor to open new business and academic opportunity suggesting different interpretations of the problem, challenging the system boundary, exploring the system getting buy-in for the project, visualising the system (Yearworth, M, Edwards, G, Davis, JP, Burger, KM 2013).

An influence diagram is a graphical representation of a system showing how different variables in the model interact with each other. The typical influence diagram consists of a number of nodes connected by arrows. Using system network visualising tools such as NodeXL and Gephi, we can gather data about specific financial institution dealing in the main derivative market (CDS, Commodity, Equity, etc). The diagram below is simple yet very powerful and shows how the financial system transaction was concentrated by a few large financial institutions which can pose a big systemic risk if one of these central nodes were to fail (2007). This information would be very helpful to the regulators to spot how stress in one of these key institutions will propagate throughout the system.

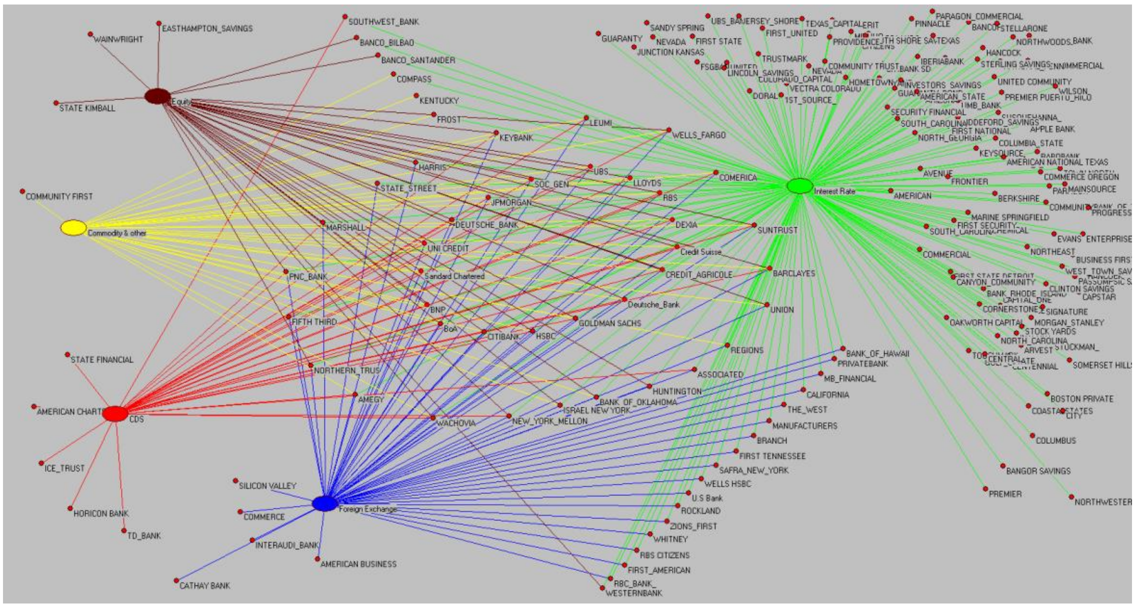


Figure 1.10 Lines indicate interest rate (green), Forex (blue), equity (maroon), CDS (red) commodity (yellow); circles indicate broker-dealers in all markets.

Chapter 2 Literature Review

In this chapter we review literature related to all aspects of the project. The first section 'Introducing risk and risk management' briefly introduces the general concept, terms and issues around risk and risk management.

The second section 'Risk, emotions and decision making' expands upon these themes in depth and discusses literature regarding emotions, neuroeconomics and decision-making relevant to the trading game experiments described in Chapter 3.

The third section 'Risk assessment, perception, aversion and tolerance' brings in material particularly relevant to the questionnaire detailed in Chapters 4.

The fourth section 'Herding and the topology and dynamics of networks ' discusses literature related to the work presented in Chapter 5.

2.1 Introducing risk and risk management

Financial risks, especially for corporations with large and diverse asset portfolios, need to be carefully managed because they can cause crippling losses, even if many other parts of the business are profitable. Corporations and business are interested in derivatives markets to speculate and hedge on risks. But, perhaps ironically, derivatives must be used with care and caution because they can lead to even larger losses if risk management principles are not adhered to (Satyajit 2005).

Some definitions of risk that can be found in the literature include "any occurrence likely to adversely affect the attainment of project objective" (Hall and Hulett, 2002); "a probability, a mathematical quantity that can be measured, calculated or estimated" (Hall and Hulett, 2002); "the probability of an undesired outcome" (Hall and Hulett, 2002); "probability of failure times the severity of the consequences" (Hall and Hulett , 2002); "risk is either a condition of, or a multi-dimensional measure of, exposure to unpredictable loss or losses" (Yellman, 2000); "an undesirable situation or circumstance that has both a likelihood of occurring and a potential negative consequence on the project" (Pennock, 2002); "technical Risk denotes the risk that a project will fail to meet its performance criteria" (Pennock, 2002).

There are two major sources of risk: business and financial. Business risk is the risk that a firm is subjected to during daily operations and includes the strategic risks that reflect the risks inherent in the decisions of senior management in setting a business strategy. An example of a business risk is the risk that the economy will slow and demand for a product will fail. Also included in business risk are the macroeconomic risks that impact a firm's operations and sales. The ability to effectively manage business risk is a core competency for stronger firms.

Financial risks are the results of a firm's financial market activity. An example of financial risk is interest rate movements after the issuance of floating rate bonds. In this case, the issuing firm will be negatively impacted if the market rates increase. Another example of financial risk is suffering a loss from the default of a financial obligation.

Several recent and significant events have highlighted the volatility of financial markets, thereby raising the need for financial risk management systems, as later described in this work in Chapters 3, 4 and 5. Example of extreme market events include the fixed exchange rate broke down (1971); oil crisis of 1973 leading to high inflation and volatile interest rates; the 1987: Black Monday, which saw a 23% decline in US stock prices; problems in Asian markets in 1989 and 1997 that delimited and decimated Asian equity markets; the Russian debt default of 1998 and the collapse of the Long Term Capital Management hedge fund; the 2001 US equity market collapse after the September 11 terrorist attacks; the 2008 financial crisis and subsequent Great Recession.

It is evident that these events caused significant increases in volatility which resulted in huge financial losses. In addition, firms have recently become more exposed to economic and financial variables. Two major factors have led to increasing the sensitivity to these financial factors: deregulation and globalisation. Before the 1970s, the banking industry was more heavily regulated, and regulations such as interest rate ceiling reduced bank exposure to interest rate fluctuations.

Deregulation in the banks, therefore, led to increase in interest rate sensitivity. Globalisation led to companies doing business outside of their respective domestic borders, causing these firms to have more exposure to currency changes and international competition. These changes have increased the importance of risk management because financial institutions are now exposed to a wider variety of risks.

It is worth noting that economic growth depends on taking risks so, therefore, risk should not be viewed as something we must avoid, but as something, we must manage carefully. Appropriate use and development of financial risk management tools as described in Chapters 3, 4 and 5 serve to provide protection against potential future losses.

2.1.1 Defining, measuring and managing financial risk

What is the best way to manage the risk associated with investments and financial decisions? The process of handling risks during a project is known as risk management, and there are many tools and communication techniques for effectively managing financial risks, which can be utilised by one person or a whole team as the size and complexity of a project demands. Furthermore, scientific processes used in risk measurement are constantly evolving and updating to make more accurate risk measures, and novel methods used to quantify the many dimensions involved in risk management decisions.

Some definitions of risk management include "An organised process to identify what can go wrong, to quantify and assess associated risks, and to implement/control the appropriate approach for preventing or handling each risk identified" (Hall and Hulett, 2002); "The systematic and iterative optimisation of the project resources, performed according to the established project risk management policy, which describes the organisation’s attitude towards risks" (Yellman, 2000); "The Risk Management Process consists of all the project activities related to the identification, assessment, reduction and acceptance of risks" (Yellman, 2000); "The identification, analysis, prioritisation, mitigation planning, and monitoring and control of events which have a potential of causing unwanted change" (Guenterberg, 2000).

In addition to these definitions, there are a number of terms that help risk managers with their work. One of the major tools used to manage market, credit and operational risk is the **value at risk** (VaR) measure. VaR is defined as the maximum loss over a defined period of time at a stated level of confidence, given normal market conditions. VaR corresponds to the loss in the tail of the return distribution measure utilised by many financial insinuations. Jorion (2007) presented a comprehensive and highly readable reference on VaR and its use in the banking industry. Dowd (1998) provided a slightly more advanced treatment of the theory and applications of VaR. The most widely known commercial application of the VaR approach is the RiskMetrics methodology presented in Zumbach (2006).

Other notable risk management tools include the a **stop loss limit** that seeks to limit the amount of loss on a position by eliminating the position after a cumulative loss threshold has been exceeded. It is a control mechanism that functions ex-post (i.e. after the loss has occurred). This measure is easy to calculate, easy to explain, and can be aggregated across assets, hence, it allows for risk to be measured a cross an entire portfolio/institution (Kathryn, 2008). Kathryn looked at the application of a simple stop-loss strategy applied to an arbitrary portfolio strategy in the US markets over the 54-year period January 1950 to December 2004. Applied to the whole 54-year period, the study found that this simple stop-loss strategy provided higher returns while at the same time limiting losses substantially.

A **notional limit** is a limit on the notional amount invested in a position or asset. This measure fails to explain the risk of apposition to change in risk factors. For example, two bonds with the same notional amount will likely have two different risk levels. Notional limits are easy to calculate and explain, but cannot be aggregated across assets.

Exposure limits are limits to risk factor exposures. For interest rates, the application exposure is duration. For equity market exposure, the relevant exposure is beta. For options, a major exposure is delta. While these measures identify the exposure of an asset to an applicable risk factor, the measure fails to quantify the volatility of the risk factors and the correlations between factors. Exposure limits are difficult to calculate, difficult to explain and cannot be combined across assets.

How should companies use such risk metrics? Statistical techniques such as VaR and others described above can measure and quantify financial risk for firm or specific investment portfolio over a specific time frame. Risk metrics like VaR can provide managers and traders with appropriate targets, and help to manage wider risks within a company. But risk metrics are not perfect, may be overly narrow in scope (Zumbach, 2006) and the fundamental theories about individual decision-making on which some are based has been questioned. Furthermore, many metrics are subject to 'gaming', a form of manipulation, which can limit their value.

Outward-facing risk metrics can also have knock-on effects in the wider financial market, as companies with a stake or relationship with a firm adjust their trades or positions in response to new, potentially volatile information. This can lead to predatory trading, where rival companies actively trade and take up positions to hurt the profile or positions of another, typically larger company. Predatory trading is hard to predict because it involves multiple players, and so it is very challenging to include in accurate risk metrics. These concepts are explored further in the research sections of this thesis in Chapters 3-5.

2.1.2 Risk management failures

Risk management failure results from not correctly recognising, measuring and/or monitoring risks, as well not appropriately communicating risks to top management. Mismeasurement of risk can result from recognising how return distributions change, using subjective inputs concerning rate events, and failing to take all risks into account. The role of risk management involves performing tasks such as assessing all risks faced by the firm, communicating these risks to risk-taking decision makers, and monitoring and managing these risks so that the organisation takes only the necessary amount of risk. These factors have informed the risk management questionnaire as described in Chapter 4.

The risk management process focuses on the output of particular risk metric (e.g. the VaR for the firm) and attempts to keep the measure at a specific target amount. When a given risk measure is above the chosen target, the firm should decrease risk. The risk management process usually evaluates several risk metrics (e.g. duration, beta) simultaneously, which as informed the work in Chapters 3-5.

A large loss is not necessarily an indication of risk management failure. As long as risk mangers understand and are prepared for the possibility of loss, then the implanted risk management was successful. However, risk management should recognise that larger losses are possible and develop contingency plans. The process of risk management can fail if one or more of the following events occur: not measuring known risks correctly; not recognising certain risks; not communicating risks to top management; not monitoring risk adequately; not using the appropriate risk metrics.

Risk mismanagement can occur when risk mangers do not understand the distribution of returns of single risky position or the relationships of the distributions among different positions. Understanding the distribution of given position means being able to identify the underlying return distribution and probabilities associated with that particular distribution. Understanding the relationship among return distributions means being able to identify how risky positions are correlated. In both cases, it is crucial to understand the degree to which return distributions and/or correlations can change over time. It is well known, for example, that correlation tends to increase during times of stress (Jorge, 2011).

One of the key issue for risk mangers is the occurrence of extreme events, which are events that occur with low frequency, but high severity (Diebold, 2009). Estimates of these rare events require a degree of subjectivity, which clearly has the potential for mismeasurement. Unfortunately, company politics can play a role in reducing the accuracy of risk estimates since some departments may wish to understate risks by using subjective measures. Mismeasurement can also occur from ignoring relevant risks, knowing about a risk, but failing to properly incorporate it into risk models, and failing to discover all risks.

A firm ignores known risks by failing to realise how various position risks can lead to a potential disaster. This was the case when Long Term Capital Management (LTCM) failed to recognise that high-yield Russian debt had not only default risk, but also currency risk, sovereign risk and counterparty risk. For example, the mangers of LTCM had thought they had hedged currency risk by selling Roubles forward, but the Russian banks on the other sides of the transaction failed during the 1998 Russian crisis (Jorion,2000).

One of the severe consequences of either ignoring or not adequately using data in risk models is that the firm might expand its operations in areas where risks are not being properly accounted for, make a risk allocation to head office, but then the firm ignores the data generated by this trading office and does not monitor to see if allocation adjustments are needed. Another example is blindly accepting a given assumption (i.e. AAA-rated assets are a very low risk) and ignoring data that would indicate the contrary.

Another risk that is often ignored is increasing correlation during a time of crisis (Das, 2005). Not recognising the possibility of increasing correlations could potentially lead to large losses. Consider, for example, the correlation between credit risk and market risk for banks. In the recent credit crisis, market risk caused decreases in security values issued through securitisation, and credit risk cased a decrease in the utilisation of securitization. The important point is that firms must use all available data to adequately measure all risks and relationship among risks. These principles informed work described in Chapters 3-5.

2.1.3 Risk management and effective communication

Risk management is not just about avoiding huge pitfalls. Whilst this is important, it is also concerned with developing strategies to make optimal decisions to maximise asset values held by the organisation. But risk management techniques, like other endeavours in a company, cannot be optimally executed unless tactics and strategic overview can be effectively communicated to the people responsible for making risk-management decisions.

For example, middle management and (possibly external) intermediaries must be fully briefed on desired outcomes, targets and barriers must be set, and feedback loops established to prevent rogue activities. These could be done in the office, or at company ‘away days', or off-site meetings devoted to the topic. Risk management actions can be damaged by poor communication, and senior management must be wary of getting a false sense of security from erroneous or potentially misleading information. Risks pervade organisations from top to bottom, and safeguards and checking processes should be employed to communicate risk management processes, tactics and strategy.

A key factor that risk managers need to take into account is how the risk profile of a portfolio can change over time – even when no active trades are being carried out. The prices and properties of certain investments can shift for many reasons, such as changes in interest rates (national or federal), or changes in political leadership, or influential economic outlooks. Some securities also have complex relationships with certain market variables, such as price increases as interest rate decline in one range, and then disproportionate declines as interest rates decline even more and outside of the initial range.

For instance, the pricing of subprime derivatives is now a classic example of moving risk exposure. The ABX (asset-backed securities) indices for a long time showed no variation for top, triple AAArates of securitisation. This changed dramatically during the 2008 financial crisis when the ratings provided by the main agencies (e.g. Moody's, Standard & Poor's) declined suddenly after being stable for a long time. The result was that risk managers (and many others) who had placed too much reliance on the top-rated assets incurred huge losses in a short space of time. Hence, risk managers need to be aware of how quickly risks can change over time and have a comprehensive knowledge of market conditions and the mechanisms by which these changes can occur. In addition, and as any good manager will tell you – having realistic and practical contingency plans (including crisis communications) is essential and good business practice.

A key principle that risk managers should be in mind is that the act of analysing and monitoring risks can change their behaviours as they are exposed to new information, which is expanded upon in the herd behaviour analysis in Chapter 5. Seeing increased certainty for one factor or variable may influence the perception of uncertainty in another variable. For example, undertaking a mark-to-market (MTM, a measure of account values that can change over time) for one firm leads to information and fluctuations and adjustments in other firms, changing their risk profiles in a way that may increase (or decrease) risk.

However, it's worth remembering that managing risk is about managing risks – not negating them entirely or suppressing innovative ways of trading and transferring assets. Overzealous or poorly thought out risk management should be avoided and it is up to senior managers to allow staff the freedom to innovate and manage risks in their daily duties – this trade-off between safety and flexibility is one of many associated with risk in the financial world – and a pay structure should be set up that promotes effective but profitable risk management. These principles informed the rationale behind the risk management tool developed and described in Chapter 4.

2.1.4 Conclusions - integrating multiple risk management techniques

Companies should strive to constantly improve their risk management processes, because it is an evolving field like many others. But large organisations typically do not have just one risk (or set of risks) to deal with. To adequately manage its risk profile, accompanies need to create a risk profile that works across the entire organisation's departments. However, in the classic case of 'apples vs. oranges', firms need to handle the complex task of allocating risk budgets to each division and equating different risk values and types of risk into a consistent and stable monetary framework.

For some time, a portfolio-based technique has been utilised from the theory developed by Markowitz, Sharpe, Treynor, Lintner, and Mosin (1957) that has been used by asset managers to manage risk. This is a 'top-down' approach, where the measure of total risk (now called 'integrated risk') is made up of the variance in asset returns. This total risk can then be sub-divided into systematic risk (of the whole market, where beta is a function of the risk, also called 'undiversifiable risk') and unsystematic risk (to a specific company, also known as 'undiversifiable risk'), or divided even more finely as used in multifactor models.

The consequences of this top-down perspective have been various risk-allocation applications like Grinold and Kahn (1999) and Litterman (2008). But these applications do not specify the total capital necessary for specific operations because they are portfolio-based and do not deal with the real capital values of individual assets. So in seeking a more integrated risk measurement framework, financial establishments have looked to a more 'bottom-up' approach from the banking world, where risk measures are based on factors and subfactors at the individual trading desk level. These models have utilised VaR in factors such as interest rates, equity, currency, and commodity market risks all calculated and consolidated into one overall market risk number. After these factors, additional ones including liquidity risk, credit risk and operational risk were added.

These factors are integrated with the holistic views that allocation of valuable capital (which can be scarce for banks) can only be exercised well if all risks at desk level can be practically collated. There are many ways to do this, such as described by Dowd (1998) and Jorion (2007) who have each developed VaR-based frameworks. A high-level overview has also been designed by Duffie and Singleton (2003) that integrate market and credit risk. In addition, Jobst, Gautam, and Zenios (2006) have demonstrated risk measuring frameworks that also bring together credit risk and market and scores.

At the present time, no single technique or methodology has emerged as superior or dominant – they may well not be a 'one-size-fits-all' way of integrating multiple risk factors that suit all organisations of all types and sizes. Indeed, the top-down portfolio based methods and more modern 'bottom-up' desk-based techniques have begun to converge in order to develop the very best risk management tools. Over the last two decades, research into risk measurement has developed into a field of its own as new measures and methods have been tried and tested. Measures that were only applicable to one area e.g. market risk, can now be used in operational and credit risk management.

The relative success of these new methods, a culmination of work by everyone from academics to regulators, can then in the future be validated (or not) by their performance before, during and after future times of increased volatility and potential financial disasters. These were significant motivating factors in designing the experiments, models and risk-management questionnaire described in Chapters 3 and 4.

2.2 Introducing risk, emotions and decision making

This section of the literature review introduces terms, concepts and background relevant to the risk, emotion and trading experiments described in Chapter 3.

Finding the key to being a successful trader is a huge business. Much effort within industry and academia has been devoted to uncovering any insight into how people can make more effective investment decisions. A key question is how our emotional state affects investment decisions and whether our emotions ultimately aid, or degrade, our trading performance.

In addition to the question of emotions, there is the one regarding making rational decisions: are we always rational? The world and the people within it are not always guided by rational behaviour. Outright intelligence, propensity to take risks, as well as access to information limit the application of Bayesian-type algorithms to determine decision-making. Bayesian-style social learning can still emerge, and is likely to because people like to use rational ‘rules of thumb' and their own personal practical quick fixes to whatever works (heuristics). Therefore, herding can occur because people tend to use easy decision-making tools, including that others are likely to know more about e.g. the long-term values of certain assets.

Social and psychological factors like peer pressure can also encourage individuals to follow other people’s decisions — even when presented with clearly contradictory data. The picture is complicated by a person’s age, gender and personality traits that can affect how easily they are swayed by social-psychological influences. Regarding personality traits, it has been reported that their importance is consistent with other analyses that focus on the role of emotions in financial and economic decision-making (Elster 1996; Kamstra et al. 2003; Lo et al. 2005; Baddeley 2010).

2.2.1 Limitations of traditional models in finance

Traditional finance models have allowed little room for the role of emotion in decision-making. Indeed, they represent individuals as interested agents who attempt to optimise to the best of their ability in the face of constraints on resources. Markets are viewed as efficient, meaning that price coincides with the fundamental value and is influenced by supply and demand as exemplified by the efficient market hypothesis (Fishburn, 1988).

These traditional finance theories make three fundamental assumptions about individuals. Firstly, individuals have rational preferences across possible outcomes. Secondly, they strive to maximise utility in that they wish to maximise the total value derived from the available money. Finally, they make independent decisions based on all relevant information. Traditional finance models thus hold the ‘Homo-economicus' (Drucker, 1939) view of individuals as rational, unbiased and unemotional individuals. Decision-makers are to consider all relevant information and come up with the best decision under the circumstances.

However, in reality we have limited processing ability and therefore use heuristics (rules of thumb, practical ways to get things done), are prone to inattention and biases (Deaves, Dine, & Horton, 2006). Moreover, contrary to traditional finance models’ predictions of an efficient market based on rational decisions, Daniel et al. (2002) found that investors systematically deviate from optimal trading patterns.

The field of behavioural finance challenges the assumptions of traditional finance theories by incorporating these observable, systematic departures from rationality into finance models. The goal of behavioural finance is to understand psychological biases that affect investment decision (Peterson, 2007) because reducing these errors would lessen their effect on financial decisions, leading to potential improvement such as greater investment results (Kuhnen & Knutson, 2005).

Behavioural finance researchers posit that because human information processing capacity is finite there is a need for abbreviation of decision processes or heuristics to arrive at decisions in the most cognitively efficient way (Tversky & Kahneman, 1974). This heuristic simplification process, according to Hirshleifer (2001), can explain most psychological biases including emotion-based judgements. Such emotional biases potentially lead to irrational decision-making (Kahneman & Riepe, 1998). As such, inherent to behavioural economic theories, is the view that emotions hinder financial decision-making and should be countered and controlled so as to attain the most efficient trading performance.

According to Kahneman and Tversky's (1979) behavioural model of prospect theory, individuals make decisions based on the potential value of losses and gains rather than final outcome. Decision-makers set a reference point for each decision and from this point evaluate potential outcomes. Lesser outcomes than the reference point are considered as losses and greater ones as gains. The resulting S-shaped value function is asymmetrical: loss hurts more than gain feels good, and these are also dependent on whether they were followed by a loss or a gain (Tversky & Kahneman, 1991). As such, individuals are not uniformly risk averse as suggested by traditional models (Bowman, 1984) but adopt a mixture of risk seeking and risk averse behaviours. When returns are below the reference point most individuals are risk seeking, and when returns are above the reference point most are risk averse (Fiegenbaum and Thomas, 1988).

Assessment of individual risk attitude has been central in financial decision-making theory and practice (Cho & Lee, 2006). Fellner and Maciejovsky (2007) found that individual risk attitude was systematically related to market behaviour. High-risk aversion is associated with lower observed market activity and more cautious behaviour thus translating in lower returns and volatility (Barber & Odean, 1999). As such, although behavioural finance has now acknowledged and integrated the effect of psychological and emotional factors, such as risk aversion, it would appear that they still perceive emotions as hindering decision-making, approaching emotions as bias inducers.

2.2.2 The introduction and influence of neuroscience

Neo-classical economics has eschewed the investigation of emotions in favour of portraying decision-makers as 'rational' and unbounded in terms of mental resources. Newer developments in behavioural economics and emotional finance have taken an interdisciplinary route, embedding theories and findings surrounding individual differences in decision-making from psychology with models of human behaviour developed within economics.

Neuroeconomics is a recent field, whereby methods within cognitive neuroscience and psychophysiology have been included in empirical investigations into economic models of choice and behaviour to develop more advanced models that take account how humans actually behave and manage risk in real-world decision environments. Within these newer fields of research, economists have mostly relied on a psychoanalytic approaches to understanding the effect of emotions on trading decisions.

In their research into the dot.com bubble of the 21st century, (Taffler and Tuckett 2005) pioneered the field of emotional finance by introducing Freud’s (1911, 1916) theory of psychoanalysis and 'phantasy' objects to financial decision-making. These authors theorised that investors let a range of unconscious and infantile emotions dictate their actions regarding dot.com stocks, rather than knowledge of company fundamental or future growth potential. The collective behaviour of these emotional investments leads to 'herding' behaviour, exacerbating market bubbles. At this stage, the high level of input from emotion leads to overconfidence (Shefrin, 2007). When the bubble 'bursts', high levels of negative emotions such as regret and guilt further impact upon investment decisions (Taffler and Tuckett, 2005, 2011).

High levels of emotional attachment to investment options have been associated with several decision biases. Fairchild (2009) found that company managers in corporate finance organisations would emotionally attach themselves to particular project and experience an endowment effect whereby managers would over-invest in particular options and repeatedly ignore risks of losing capital if the project was successful in its initial stages. These findings were supported by Eshraghi and Taffler (2009) who investigated similar behaviour in hedge fund managers. Therefore, many economists posit that unconscious emotions have a detrimental effect on trading decisions.

Research into the neuropsychological underpinning of emotions has lead psychologists to perceive emotions as facilitators. Indeed, neuroscientific research has introduced a process theory of decision-making based on anticipation of various emotional reactions to outcomes (Bossaerts, 2009). Emotions are posited to be an integral part of reasoned decision-making and are believed to actually improve the process (Bault, Coricelli, & Rustichini, 2008).

In fact, Bechara and Damasio (2005) suggest that emotional processes guide reasoned decision-making. For complex choices or when the stakes are high, cognitive processes are unable to lead to a decision. Damasio's somatic marker hypothesis (SMH) describes somatic markers as the association between relevant stimuli and induced physiological affective states (Bechara, Damasio, and Damasio, 2000) which recur and lead these cognitive processes. The somatic marker association is thought to be processed in the ventromedial prefrontal cortex (vmPFC) (Damasio, 1989). This neurological region was found to be the interface between visceral reaction and higher cognitive functions and thus postulated to hold the association between the facts that compose a given situation and the emotions previously paired with it (Damasio & Damasio, 1994).

Empirical support for the SMH has been based on the Iowa Gambling Task (IGT) an experimental paradigm designed to measure decision-making (Bechara, Tranel, Damasio, & Damasio, 1996). During the IGT researchers assessed individual participant's levels of autonomic arousal through the galvanic skin response (GSR) measurements. GSR is a method of measuring electrical conductance of the skin which varies depending on the state of the epidermal sweat glands (Boucsein, 2012). As sweating is controlled by the sympathetic nervous system, GSR is used as an indicator of psychological and physiological arousal (Martini & Bartholomew, 2001).

Research has consistently found that successful performance on the IGT is correlated with the development of somatic marker signals as indexed by anticipatory GSR in healthy control participants. Crucially, patients with vmPFC lesions would consistently opt for the wrong decision and fail to express emotional anticipation when making a risky decision (Bechara, Tranel, & Damasio, 2000), thus indicating the fundamental and beneficial role of anticipatory GSR in decision-making. Furthermore, in a review of the literature on decision-making measuring GSR, Dawson et al. (2011) concluded that when making a significant decision or when presented with a stimulus with a possible negative consequence in anticipation of that outcome, GSR are likely to occur.

Thus, a fundamentally different account of the role of emotion is given by neuropsychological research and theories. According to the SMH, emotions in the form of anticipatory GSR are important and functional cues, signalling possible negative outcomes without which dysfunctional decisions are made.

Therefore, the viewpoints of psychologists and many economists are conflicted. Using a neuroeconomic approach will permit exploration of psychological and physiological mechanisms involved in investment decision-making and inform this apparent contradiction. Potential real-world applications of work exploring this apparent discrepancy include an evolved understanding of effective choice strategies in trading environments. This was a motivation in designing our trading game with physiological measurements as described in Chapter 3.

2.2.3 Measuring emotions in financial market decision-making experiments

Although recent neuroscientific studies have examined in great depth the process by which emotions influence decision-making under conditions of risk and uncertainty, few studies have examined the specificity of financial decision-making. It is important to examine emotions in financial decision-making specifically to assess whether emotions are particularly hindering to decision-making, as posited by financial theories, or whether emotions in financial decisions are facilitators as hypothesised by the SMH.

Lo and Repin (2002) are among the few to have examined trading patterns and daily affective reactions. They measured GSR of financial securities traders during their trading activities. They found that during salient market events, GSR measurements were elevated, suggesting that emotional responses are a significant factor in real-time financial processing. GSR responses were found to be significantly different during transient market events relative to no-event control periods, both before the event (anticipatory) and after the event (post). Interestingly, contrary to the SMH predictions they did not find any difference between anticipatory and post GSR.

SMH theory emphasises the cueing role of emotions in decision-making, so anticipatory GSR would be expected to have been heightened in comparison to post GSR as somatic markers signal a potential negative outcome. Lo and Repin (2002) concluded that this lack of difference implied that their measures were unsuccessful in assessing anticipatory emotional responses and potentially significant methodological issues were highlighted. Namely, their inability to relate psychophysiological responses directly to a trader's financial gains and losses. Furthermore, their window for anticipatory and post GSR was 10 seconds – meaning that the two responses could possibly overlap, thus offering another possible explanation for the lack of difference between anticipatory and post GSR. Moreover, the sample size was very small (10 professional traders). While this study has brought forth important findings, for these to be fully taken into account, they need to be replicated in a methodologically sound manner.

In another study, using a different paradigm and a bigger sample of 80 future trader volunteers, Lo et al. (2005) investigated further the link they had previously established between emotional reactivity and trading performance. Using daily emotional state surveys over a five-week period they constructed measures of affective states for each participant and correlated them to profit and losses. Reporting extreme emotional responses whether negative or positive was found to be counterproductive from the perspective of financial trading performance. The authors thus propose that the affective state of the decision-maker may characterise dysfunctional financial decision-making. A two-dimensional approach to affect examining both valence (intrinsic attractiveness or averseness) and arousal (the strength of emotional response) has been frequently suggested in the literature (Mano, 1992; Heller, 1990; Lang, Bradley, & Cuthbert, 1990). Such representation would lead to a greater understanding of the interaction between affective states and decision-making (Mano, 1994).

To achieve a greater understanding of the role of emotions in financial decisions, it is important to use a wide range of measures of emotions (Lane, 2008). Lane and Schwartz (1987) have established a five-level model of emotions comprising, in ascending order: bodily sensations, action tendencies, discrete emotions, blends of emotions, and blends of emotions in self and others. These five levels have since been conceptualised through the implicit and explicit continuum in which each level is inter-related yet independent. As we wish to examine contradictory approaches to emotions, it appears essential for us to assess a number of these different levels. Further details about how these were integrated into the experiments can be found in Chapters 3 and 4.

2.2.4 Integrating with other theories about decision-making

As we have seen, economists focus on the detrimental effect of emotions in financial decision-making, while psychologist emphasises the crucial and beneficial role of emotions in this process. According to Camerer et al. (2004) a biological basis for behaviour in neuroscience combined with financial theories, such as prospect theory, may provide some unification across these approaches. These authors believe that neuroscience should inform economic analysis (Camerer, Loewenstein, and Prelec, 2005). They conclude that side-stepping biological and cognitive sciences that focus on the brain, which is the building block of the economic system, may prove to be dangerous to the field (Camerer, Loewenstein, & Prelec, 2004).

Indeed, recent neuroscientific research such as work by Lo and colleagues (2002, 2005) has been remarkable in offering an insight into the actual mechanism by which emotions influence financial decision-making. However, as we have seen these studies are limited and crucially do not integrate past financial theories.

Damasio's hypothesis is not the only game in town when it comes to theories of decision-making. In 1996, Steven Sloman introduced another interpretation of dual processing theory: that a phenomenon can occur in two different ways or by two different processes e.g. an implicit (automatic) unconscious process, and an explicit (controlled) conscious process. Sloman (1996) theorises that the associative reasoning (connecting and integrating thought patterns) leads to stimuli, which the brain then arranges into logical groups of information depending on how often they occur. In this theory, organisation occurs via experiences in direct proportion to the similarity that things that have happened in the past.

Kahneman (2003) provided yet another hypothesis, which differentiates two types of processing into a) intuition, and b) reasoning. Intuition (sometimes called system 1), is similar to associative thinking, has fast and automatic aspects, and features strong emotional links to reasoning processes because it is based on past habits that are difficult to modify. Reasoning (sometimes called system 2), works at a slower speed and is subject to conscious moods and judgments and attitudes.

It is thought that system 2 is relatively recent in evolutionary terms, and, with present knowledge, is considered specific to humans. This rule-based system (also called a rational analytical system) does its work using short-term memory and so is slower than the automatic system 1, and the demands of this conscious, hypothetical thinking system 2 leads to limited capacity, probably because of the energetic demands of such a system.

There are therefore different hypotheses around the idea that there are two systems involved in decision making in the brain – in general that one is automatic and unconscious, and the other influenced by conscious judgement. Some researchers prefer to refer to these systems as 'implicit' (as in system 1) or 'explicit' as in system 2. Researchers such as Goel et al. (2000) highlight the more functional side at the expense of the consciousness factor. Later, Goel and Dolan (2003) used functional magnetic resonance imaging (fMRI) to find neurological evidence for the dual processing theory of human decision making. They found that the two types of reasoning could be sourced to different parts of the brain: reasoning based on content activated the left temporal hemisphere, whereas more the parietal system was activated in more abstract thinking.

Goel and Dolan also found that the different mental processes were competing for control of the problems experienced by study participants. The prefrontal cortex was heavily involved in detecting and resolving conflicts (characteristics of system 2), but the ventral medial prefrontal cortex (vmPFC) and medial orbitofrontal are known to be associated with more intuitive, system 1-type responses, was also activated, and was in competition with the prefrontal cortex. The vmPFC activation is associated with suppressing emotional responses., and these findings thus point to the vmPFC as a key area in judging preferences in decision making, in that it has a role in the activation/reactivation of associations related to the emotions connected with past events, such as the adrenalin rush of a gambling win or successful stock trade. These are the types of emotions and reactions that will determine how our participants would react in our simulated trading game, described in Chapter 3.

2.2.5 Decision-making research in economics

As pointed out by Lo and Repin (2002), traditional research into the behaviour of financial markets was built upon the bedrock of the efficient markets hypothesis (EMH) in which market prices are assumed to be determined by the actions of an infinite number of fully-rational, unbiased, homogeneous, unemotional expected utility-maximising price-taking investors: collectively, the forces of supply and demand dictate stock prices that are always very close to fundamental prices (prices are informationally efficient). Thus, the EMH, together with the Markowitz portfolio theory (MPT), emphasises passive trading (for example, investors should hold index/tracker type funds and should only react to ’news’ that comes to all market participants at the same time), and that investors cannot outperform the market on average.

Recently, behavioural economists have recognised that the financial markets are populated by real-world traders, subject to human psychological biases, bounded rationality and emotions. This implies that there is a role for active trading, investors may react in a psychologically biased and emotional manner, and that market prices often diverge dramatically (either positively or negatively) from fundamental values. Thus, markets are informationally inefficient, and there is the possibility for traders to outperform the market with careful trading strategies (and hence to underperform if they trade badly!).

A major contribution of our work is that we consider experimentally the relationship between risk preferences, emotions (both conscious and unconscious) and traders’ performance in our trading game (see Chapter 3). A huge debate exists in the literature on whether emotions improve or detract from investors' performance in the financial markets. Some researchers argue that investor emotions worsen traders' performance (for example see Lo, Repin and Steenberger 2005; Lucey and Dowling 2004, 2005; Shiv et al 2005; Gray 1999; Meyer et al 1990; Lerner and Keltner 2001; Schunk and Betsch 2006). On the other hand, Ackert and Deaves (2010), and Ackert, Church and Deaves (2003) argue that emotions may actually enhance investors' performance in the financial markets, since emotions are a 'spur to action' in the face of complex and informationally-opaque decision-making. This notion is supported by Seo and Barrett (2007) who studied the effect of emotions on investment club members. In contrast to financial economists, psychologists have long recognised that, far from being a detraction, emotions are a necessary and integral part of sound decision-making.

The debate is summarised neatly by Fenton-O'Creevy et al (2011). They argue that the key factor to consider is whether emotions are incidental or integral to the decision. Incidental emotions can interfere with the 'rational assessment of information and risk' (see Lerner and Keltner 2000. On the other hand, according to O'Creevy, "By contrast, accounts of emotions as information focus primarily on the role of integral emotions in rapidly, often unconsciously, encapsulating the intersection of prior and current relevant experience (e.g. Bechara and Damasio 2005)." Noting that incidental and integral emotions may not be in contradiction, O'Creevy et al note that traders' emotion-regulation may become important, with traders accentuating the integral, and reducing the incidental emotions.

In our experiment (Chapter 3), we consider both conscious (through the PANAS), and unconscious emotions (through GSR measurements during the trading game). In this chapter, we focus on the effects of unconscious emotions on trading performance in a bear market.

2.2.5 Research on decision-making and framing

The relationship between implicit emotion and choice behaviour is not linear but dependent on context, and framing effects should be considered. The classic framing experiments (Tversky and Kahneman, 1981) provide participants with two risky choices where the outcomes for each are exactly the same, but one choice is framed in terms of gains (e.g., save 200 people from disease or take a 1/3 chance to save 600) and the other in terms of losses (lose 400 people to disease or take a

1/3 chance that no one will die). Participants are significantly more likely to be risk-averse in the gain frame (i.e. save the 200 people) but, in the loss frame, be risk-seeking (i.e. choose to gamble to potentially save them all).

Emotions affect our susceptibility to these framing effects. Conscious emotions mediate the effect of framing on opinions on immigration (Lecheler, Bos & Vliegenthart, 2015) and health messages (Covey, 2014) and (implicit) levels of skin conductance response to an expected electric shock is moderated by whether the shock is framed within a positive or negative manner (Ring, 2015).

Hinvest, Brosnan, Rogers and Hodgson (2014) found that although a unitary brain system was involved in risky decisions regardless of framing, the frame itself elicited varying levels of activity in different neural regions within that system. Specifically, preference elicitation involving valuation of single gambles recruited regions associated with working memory and mathematical calculation (lateral prefrontal cortex and inferior parietal cortex), whereas preference elicitation between two gambles recruited more emotional areas of the brain (anterior insula), thus cognitive and emotional mechanisms have different levels of input into decision-making across different frames. Thus, in the current study, we could hypothesise that the two frames (i.e. the two share trends) would receive different levels of input from cognitive and, critically, emotional mechanisms leading to different patterns of implicit emotional arousal and decision-making performance. Measurement of the feedback-related negativity (FRN) after experimental choices can also shed some light on how emotion may affect integration of feedback into future decision strategies, because the strength of the FRN is impacted by current emotional status (Mai, Peng and Wang, 2015).

2.2.6 Research on decision-making and arousal

Increasing the effectiveness of trading behaviour is big business, with a vast host of companies and websites aiming to offer support in developing an individual to make more money trading. The effect of emotions on trading performance is a common theme within this training. Many of these approaches are, at best, loosely based on valid empirical research. Thus, research into how emotion effects trading performance is highly lucrative and essential to inform effective training.

Lo and Repin (2002, 2005) and Fenton-O’Creevy et al. (2012) measured a range of psychophysical signals including GSR and heart rate variability (HRV) in professional traders in live trading environments and found that characteristics of the trading environment such as making positive returns and market volatility were associated with significant changes to arousal state. Furthermore, arousal was positively associated with amount of trading experience (O'Creevy et al., 2012; Lo and Repin, 2002) aligning with the findings that experienced traders are more able to regulate their emotions and turn felt emotions into positive strategies (O'Creevy, Soane, Nicholson and Willman, 2011). Thus it is not the simple linear case that emotions are "bad" for trading.

Emotion regulation strategies designed to minimise variability in emotion have been found to increase the optimality of trading decisions (O'Creevy, Soane, Nicholson and Willman, 2011; Hariharan, Adam, Astor and Weinhardt, 2015). There is some emerging work that electroencephalogram (EEG) could be used to identify whether an individual is in a positive or negative emotional state which, alongside GSR, would provide measurements of both an individuals emotional valence and level of arousal (Kim et al., 2013; Petrantonakis & Hadjileontiadis, 2010). It will be interesting to see how this field will develop.

Indeed, there has been extensive research analysing the effects of anxiety on performance (see, for example, Cassady and Johnson 2001; Stossel 2014; Eysenck et al 2007. Furthermore, there is a growing area of psychology research that suggests that anxiety may lead to paralysis. Rauh and Seccia (2006) present a theoretical model in which the relationship between anxiety and performance is an inverted U-shape (a low level of anxiety is beneficial in motivating performance: however, too much anxiety results in a reduction in performance. Hence, there is an optimal level of anxiety that maximises performance.

There is a growing area of psychology research on the relationship between anxiety and paralysis. For example, the website www.calmclinic.com/anxiety/paralysis discusses how "your emotions are a deer in headlights, unable to move or get out of the way of the impending anxiety". This may be a relevant factor in our investors' behaviour in the face of losses due to the bear market.

2.2.7 Emotions and decision-making

Personality traits and socio-psychological factors certainly affect people's decision-making abilities because many decisions are affected by people's emotions, or emotional predispositions (Elster 1996,; Baddeley 2010). Even the weather can impact upon financial decisions, as described by

Kamstra et al. (2003) and Hirshleifer and Shumway (2003) – indeed, with certain markets the phrase "the outlook can be described as gloomy" is used, which is almost identical phraseology as used in weather reports.

Using lesion patient studies, Shiv, Loewenstein, Bechara, Damasio and Damasio (2005) identify a relationship between emotional responses and enhanced risk-taking behaviour. Advanced brain-imaging techniques in the form of functional magnetic resonance imaging (fMRI) have also been used by Kuhnen and Knutson (2005) to identify divergences from expected, rational behaviours. This clearly demonstrates that emotions and moods can have significant impacts on financial and economic decisions, so it is likely that there may be certain psychological characteristics in people that also give them a predilection for herd-like behaviours. This should be little surprise to the biologically-minded: humans are animals, and herd-like behaviours have significant adaptive value. Think of shoals of fish, flocks of birds and herds (literally) of sheep that defend themselves from predators by mimicking each other's behaviour. They even do this in the absence of predators – there are no wolves or bears in the UK, for example – which indicates that higher animals get social benefits such as cohesion and feeling 'a part of the crowd' from following predominating signals – even if the information is at sometimes erroneous.

Besides evolutionary principles, theories of social psychology such as that of crowd influence and group pressure — le Bon's (1896) analysis of mob psychology for example – can shed light on the influential factors ranging from the pressure to conform (normative influence), the fear of standing out, and the desire or need to learn from other apparently more successful people. The difficulty is how to add complex social influences into successful Bayesian and non-Bayesian models – just how do you quantify conformity, or the make a fair qualitative measure of the influence that leads to it?

2.2.8 Emotions, rationality and the efficient market hypothesis

The efficient market hypothesis (EMH) states that investors are rational and trade without any emotional input, so prices reflect all available information at all times. An alternate view is presented by Shefrin (1999), who introduces human emotions back into the equation. Shefrin writes that trading is not a solely calculating endeavour, but is subject to emotional impulses, such as greed, fear and other basic (and complex) human emotions.

It can be argued that all human decisions are emotional, not rational, in nature and there are many examples that violate EMH theory, from disappointment aversion (Gul, 1991) to regret theory (Bell, 1982) and prospect theory (Kahneman and Tversky, 1974, and Tversky and Kahneman, 1992). Taffler and Tuckett (2005) have started a major paradigm shift with the development of emotional finance, and this ground-breaking new paradigm uses Freud's theory of phantastic objects as an explanation for unconscious and infantile emotions that affect investor decisions (Fairchild, 2009).

Emotional finance theory argues that entire markets, as well as individual stocks, can be analysed with the subconscious emotions that result from the belief in phantastic objects (Tuckett, 2011). Market euphoria and a subsequent crash can be viewed in terms of the emotions associated with phantastic objects. The theory has been applied to the internet mania of the late 1990s when tech stocks were argued to represent the fantasies of the people holding them (Taffler & Tuckett, 2005). Emotional finance has also been applied to the rapid growth and dramatic decline of the hedge fund industry. Hedge funds, it is argued, have become phantastic objects for people who are mesmerized by stellar gains, and the people that run them are almost deified – that is, until reality sets in and mounting losses and liquidation transform the euphoria into anger and blame (Eshraghi & Taffler, 2009).

Therefore, investor irrationality – driven by human emotions – cannot be overlooked when financial decisions are made. To effectively model herding behaviour, as described in more detail in Chapter 6, it is of critical importance to give considerable weighting towards factors that allow for people's emotional impulses.

The development of communication technology and internet increased connectivity among investors. Where information and sentiment can transfer faster and more easily among market participants, certain incidents can lead to herding and asset price bubbles. These sentiments, rumours, and opinions spread over networks of contacts between investors and market participants. Understanding the intrinsic mechanism behind herding and emotional cascade in networks is an important task, and a focus of this thesis particularly in Chapter 6.

2.3 Risk assessment, perception, aversion and tolerance

With risks come gains, but there are also losses. A common phrase on TV and print adverts for financial services products reads: “The value of your investments can go down as well as up”. People assess, perceive and handle risk in different ways, and this affects their present and subsequent decision-making abilities. People with greater wealth could be expected to take greater risks because any loss will have a smaller impact on their overall wealth, which can be measured in terms of hard currency reserves, property ownership, pension values (Brayman, 2013), future earning ability, and other factors that affect daily budgets such as insurance costs (Samuelson, 1969), and finally loans and credit cards debts. The intriguing question is: what affects how much of that wealth is a person or group willing to risk?

The first two basic factors are actual amounts and proportions of wealth. A 20% loss with a £5 million portfolio will still leave a considerable sum of £4 million to that investor. It’s a (relatively) massive loss, but £4 million is more than enough to meet daily costs well into the future. But the consequences of and investor losing £20,000 out of £100,000 – still the same proportion of 20% -- are much more significant. Note that this is not consistent with the ‘relative risk aversion’ concept that states two individuals with the same utility function are expected to feel the same disutility from a 20% loss in total wealth. Clearly, the investor losing 20% of £100,000 is much worse off, even though the proportional loss is the same. The percentage of wealth subject to risk is a key factor.

2.3.1 Assessing risk

Assessment of risk capacity can be seen as an objective evaluation of financial risk tolerance i.e. how much you can afford to lose. Hanna, Waller and Finke’s (2008) model proposes that a person’s risk profile is the sum of a) objective factors that a financial advisor can clearly see, and b) subjective factors that are best recorded through a proper risk-tolerance assessment tool. Other relevant factors include income and outgoings volatility (and the fact that people might withhold sometimes crucial information from their advisors e.g. pending divorces, debts). Time horizons (a fixed point of time in the future when certain processes will be evaluated or assumed to end) can also be included, although some such as Bodie (1995) argue that time horizons are (theoretically) not related to optimal portfolio allocation unless considered with a client’s ‘human capital’, such as their age and retirement plans, for example.

Following on from objective measures, subjective risk preferences can be thought of as the factors that influence the impact of various investments on the client’s general well-being or happiness. An identical investment can have different subjective effects on a couple that have just lost half of their life savings, compared to a couple across the street who recently doubled theirs, through a fortunate inheritance for example. A Palma and Picard (2010) review concludes that economic concepts of risk tolerance are clear enough, but measuring it is more opaque. A proper scientific evaluation of especially subjective risk factors is still in its infancy, even by financial advisors who often resort to heuristic measures in questionnaires.

Hence, a key factor in a client's inclination to take on risk is experience and knowledge of financial decision making. In this aspect, a client's level of education, independent of income and wealth, is not necessarily a good predictor of risk tolerance – many very well educated people go bankrupt. In terms of ‘risk perception', people that are more financially literate are reliably more disposed to accept financial risk. They may be better able to understand the basic principles of accepting the risk to achieve long-term financial goals, as well as being prepared for future financial performance variations.

When accepting investment risk, Dow, Da Costa and Werlang (1992) note that clients should be made aware of the likelihood or distribution of potential outcomes. People with a lower level of education or financial literacy (or less investment experience) will be less certain about the risks and tend to exhibit ‘ambiguity aversion', where a preference is shown for known risks over unknown risks where the consequences are more ambiguous.

2.3.2 Measuring risk tolerance

Risk tolerance is defined economically as a variation in future spending. So, economists utilise questions related to measuring income volatility to assess risk tolerance e.g. “would you choose between more job security and a small pay increase, or less job security with a big pay increase?” Although theoretically sound, in surveys the performance of these questions as predictors of real investment behaviour is mediocre, as found by Guillemette, Finke and Gilliam (2012), especially in volatile stock markets.

In the analysis of portfolio allocation between a high-risk, medium-risk and low-risk assets, Guillemette, Finke and Gilliam found that these income risk questions regarding investment portfolio choices are consistent with conventional utility theory (the preferences of a set of goods or services that is satisfying to the chooser). The same income risk questions were also good predictors of whether people cashed in their portfolio during the 2008 financial crisis. Other queries, such as a self-assessment of respondents’ willingness to take risks, as well as questions that gauged behavioural responses to risk were even better predictors of both response to an investment loss and portfolio preference Linciano and Soccorso (2012).

Other questions to measure financial risk do not correlate so well. In a large national data set, Grable and Lytton (2001) found that a financial risk assessment instrument did not correlate well with a series of questions relating to gambles that involved the possibility of a loss. This suggests again that there is an emotional response to potential losses, not just rational decision-making when portfolio investment choices are presented.

A number of ideas presented in Kahneman and Tversky's (1979) ‘prospect theory' (further detailed below) are important to risk tolerance assessment activities. For example, when assessing risk, people tend to begin their assessments of potential wins and losses from an arbitrary starting point – the ‘reference point' – which can be an amount invested, or asset values from or in a given time e.g. calendar year, or quarterly results. Another key aspect of prospect theory is ‘loss aversion', in that people in general respond about twice as much emotionally to a loss than to an equivalent gain. Furthermore, this emotional response is related to whether the value of the loss falls beneath the earlier reference point.

2.3.3 Predicting responses to risk

One of the benefits of behavioural questions like these is that they can help to recognise investors with greater emotional responses to risk (Loewenstein, Weber, Hsee and Welch, 2001).

The dual-self model described previously (where decisions are made by rational and emotional processes in the brain) has significant consequences in assessing a person’s risk profile. In general, people tend to overestimate their ability to use their rational mind to control their emotional responses following a loss. This has been likened to white water rafting: in calmer times you’re in

control of the boat, but when the river starts to flow much faster the (rational) paddle has much less effect on steering the boat than we'd like to think.
Can behavioural responses to risk be predicted through certain questions? Some suggest that questions that make individuals reflect on information be analytical, rather than acting on emotion or instinct, can facilitate better financial decisions. Analysis has shown that study participants who score highly on a three-question test that flexes these cognitive skills were much less likely to fall for the pitfalls seen with prospect theory (Frederick, 2005). Hence, questions along these lines could be used as an intervention to encourage a more measured 'risk composure' and avoid more impulsive responses.

But emotional responses are hard to avoid. Guillemette et al. (2012) have found that investors' responses to questions like such as "Are you more concerned about possible gains or possible losses?" are around 40% better predictors than income risk questions. Self-assessment questions can also be good predictors of real responses to financial losses, although younger subjects often overestimate their risk tolerance, as noted by Grable, McGill and Britt (2009).

An important feature of the dual-self model and risk tolerance is that we are more likely to respond emotionally to losses than to wins. Looking at a US national data set between 2006 and 2008, Browning and Finke (2015) reported that more than half of households (57%) reduced their stock holding portfolios beyond what could be explained by market returns: Such decisions will typically lead to losses as markets recover, so new avenues of research could investigate investor's attitudes before and after major financial crises, and the relative powers of 'risk composure' relative to 'risk tolerance' in shaping decision-making behaviours.

Less experienced investors who tend to have a more inadequate financial literacy are the least able to well manage emotional reactions to losses, as found by Bucher-Koenen and Ziegelmeyer (2014). Alternatively, Browning and Finke (2015) saw that immediately after the 2008 financial crisis, older respondents more likely to move their portfolio towards safer assets. This results in a phenomenon of poor long-run investment performance (known as 'dollar-weighted underperformance') whereby more investments are made in risky assets during bull markets and selling throughout bear markets (Friesen and Sapp, 2007).

2.3.4 Implications of the dual-self model and prospect theory preferences

It is clear that many investors respond to risks emotionally, particularly when considering losses. Baker and Wurgler (2007) consider this an inclination to respond to overall market sentiments (a facet of risk perception).

Another significant consequence of the dual-self model is that financial advisors can assist clients in reducing their behavioural (negatively emotional) responses to variability in their portfolio value. Winchester, Huston and Finke (2011) report that during the financial crisis, clients with a written financial plan were more likely to stick to it and less likely to move investments. Good financial advisors can, therefore, commit in writing an investment policy that fits a client's risk tolerance, thus helping to reduce emotional anxiety by sticking to and focusing on written long-term investment goals.

In addition to a lack of experience and/or financial literacy, age-related cognitive decline (including mild forms of Alzheimer’s disease) can also reduce a person’s ability to temper emotional responses to risk. In such instances when risk tolerance questionnaires display preferences towards loss aversion, an adviser would do well to construct less risky portfolio, or to utilise insurance or protection mechanisms. Along these lines, a UK study (Blake and Haig, 2014) showed a phenomenon known as ‘reckless conservatism’: they found more than half of survey respondents preferred to miss a financial goal rather than take an investment risk. Only 12% were willing to do this, even though if the only other alternative was to save more and spend less, which was preferred by only 30% of respondents.

In conclusion, assessment instruments to measure risk tolerance can work, but they must include questions that provoke emotional responses – especially to losses – to be useful and effective predictors of how people will really act during times of market volatility. Written responses to such risk-measuring tools can help advisors to assist clients in reaching their long-term goals by shielding them from the ‘emotional rollercoaster' and constructing personalised portfolios appropriate for a client's needs and personality traits. These factors have informed the design of our questionnaire as described more fully in Chapter 4.

2.3.5 Using risk assessment questionnaires

When using questionnaire or surveys to assist clients, sound financial advice (when relying solely on the questions) can only be given if the questionnaire is soundly constructed and executed well. But Palma and Picard (2010) find wide variation in how they elicit subjective risk tolerance (while noting that measures of objective risk tolerance do better). This variation results in clients, for example, receiving a recommendation for a lower risk portfolio after taking one test, and being recommended a higher risk portfolio from another test.

Criticisms of questions in such tests centre on how they can reliably (and consistently) measure willingness to accept investment risk. Questions relevant to the field, but not directly relevant to investments (about hypothetical gambles risk-taking for example) can be a distraction. As already described, many studies point to investment knowledge and experience as good predictors of the willingness to take risks. Moreover, analyses of individual questions suggest that the ability to moderate emotional responses (risk composure) and behavioural preferences like loss aversion can be very useful.

2.4. Herding and the topology and dynamics of networks

This part of the literature review is linked to simulation experiments described in Chapter 5. We begin with an introduction to network topology, centrality and network dynamics, before moving on to how network dynamics can affect herding behaviour in financial markets.

Our model of network herding and emotional cascades, along with the results of the simulation with discussion and conclusions are presented in Chapter 5.

2.4.1 The topology and dynamics of networks

Networks, consisting of nodes and edges connecting nodes, have been used to study many different problems and systems ranging from the famous Konigsburg bridge problem to elementary school children’s friendship groups, to the internet and the worldwide web (Newman, 2003). Networks have seen a resurgence of interest due to two main factors: firstly, the discovery of the scale-free property (Barabasi, Albert 1999), which can be loosely defined as a network with a degree distribution that follows a power law, has far-reaching implications and has provided a means of understanding fundamental network growth. Furthermore, the discovery has enabled computer-generated simulated networks with more realistic topologies to be created (Barabasi, Albert 2002).

It has since become a staple of analysis of all kinds of groups and networks, including financial ones, to compare and contrast the statistical mechanics of randomly connected networks to those with the scale-free property. Insight into many different situations has been gained from such approaches (Barabasi, Albert, 2002). Secondly, the ever increasing amount of computational power has allowed large networks to be analysed, and for the dynamics of such networks to be simulated.

A well-studied aspect of networks is the degree distribution, where the degree of a node is the number of edges connecting the node. In random networks, the distribution approaches a Poisson distribution, with the peak occurring at about the mean network degree. In scale-free networks, however, the degree distribution is best described by $\cancel{P(k) \sim k^{-\gamma}}$
where k is the degree, and γ is a value between 2 and 3. It is from this distribution that the scale-free property draws its name, as this distribution does not change regardless of the size of the network (Barabasi, Albert 2002).

However, whilst this is an interesting finding, the most significant finding came from successfully building such topologies. Namely, it is argued that by virtue of being able to recreate such topologies that we are able to draw greater insight into how these networks are formed. This is obviously of interest when discussing herding in the market, and how financial networks share information and gain new members, for example.

Indeed, the Barabasi-Albert algorithm for growing a scale-free network is based on preferential attachment. Quite simply put, the higher the number of connections a node has, the higher the probability is that a new node will connect to the highly connected node. This produces a scale-free network with exponents between -2 to -3 in the degree distribution. Whilst certain statistical aspects do not match the Barabasi-Albert network to real life examples (e.g. local clustering, modularity), it has proven a resilient approach, despite many different approaches having been tried in the past decade Bianconi and Barabasi (2001); Mendes, G. and da Silva (2009).

Whilst being able to understand investor networks is of utmost importance, this would require something that is not widely available: a real investor network dataset. Furthermore, all network analyses suffer from the boundary issues that inevitably occur where a cut-off point is necessary, which all social networks are subject to. Thus, in the absence of a standardised dataset that is validated as being an exemplary representation of all investor networks, there is little value in trying to determine what network evolution best mimics such a network. That is not to say that real networks should not be investigated, but rather that networks, social networks, in particular, vary greatly depending on what resources are available to construct the network in the first place. It is important to be aware of the boundary limitations, and in cases where the objective of the research is to provide generalisable findings, a simple, consistent, and simulated network suits these purposes well.

It is thus considered more pertinent to investigate a fundamental concept of topological evolution than it is to perfectly replicate a specific network topology. It is by understanding how such a concept may be suited for explaining phenomena such as herding. Either the findings will be what would be expected, or an emergent effect will arise. Such emergent effects in networks provide a lot of insight into how a real system, such as a financial trading market, behaves.

As stated, the objective of the experiments in Chapter 6 is to investigate herding. The hypothesis drawn here is that, as with the Barabasi-Albert model, investor influence networks are determined by a fitness measure. Logic would dictate that in investor influence networks, that fitness measure would be determined by outcome (e.g. if someone unknown to the investors were to consistently show that they are able to predict the market outcome, it would be expected that investors, particularly emotional ones, would try to copy this person's behaviour). A clear leader in such an event would cause a fat-tail, whereas homogeneous performance in the market would cause a random network to occur.

2.4.2 Network evolution and network dynamics

However, it is not just the topology that is of interest, there is a growing body of literature on the network dynamics. That is to say, how a property propagates through a network. The most famous of such studies come from epidemiology, where Susceptible-Infected-Recovered (SIR) or Susceptible-Infected-Susceptible models have been studied in many different contexts, such as Barthélémy, Barrat (2004) and Barthélémy, Barrat (2005). Interestingly, one would expect that the dynamic measures are very much determined by the topology (scale-free vs. random), but a seminal paper found that the dynamics behave very differently depending on the underlying method of propagation, as described in Barzel, Barabasi (2013). If we thus accept that topology is affected by performance in the market, and we consider that performance in the market is affected by emotion (for emotional investors), which is propagated as a property through a network. How then do these two interact?

As in biology where details of structure reveal the functions of a system, the topology of a network and analysis of it provides a huge amount of information about a system. The evolution of networks as studied in-depth in Albert and Barabasi (2002) can be focused to three factors: 1) preferential attachment of nodes; 2) how networks grow; 3) external and internal connections between nodes. The first two factors are necessary for scale-free networks with exponents $2 \geq \gamma \geq 3$. Furthermore, fitness can be considered a form of preferential attachment, and Bianconi and Barabasi (2001) propose a fitness parameter that where growth produces a scale-free graph with a logarithmic correction.

Researchers have attempted to model cascading of properties within networks (Buldyrev 2001, Motte 2002, Leskovec 2006, 2000) in the macroscopic (whole network) and microscopic (individual nodes) scale to ascertain how information flows. Many attempts have been made to model microscopic interactions, but it is acknowledged that in network dynamics there can be the propagation of a certain property that may or may not affect the overall topology of the system.

Borrowed from epidemiology and how infections spread, some researchers such as Lloyd (2001), Pastor (2001), Barrat (2004) and Volz (2008) have investigated propagating properties using the susceptible-infected-susceptible (SIS) model but applied to artificial networks. For example, Pastor-Satorras and Vespignani (2001) simulated a SIS epidemic spreading (via emails, file transfers) in internet systems previously identified to be scale-free (Albert and Barabasi, 1999). Research (Kephart, 1994, Maia, 2007) on random graphs has shown that above an epidemic rate critical threshold (λc) the infection persists and below the threshold, the epidemic dies out. This model reveals why epidemics take so long to die out: most viruses are eradicated within two months, but many viruses are still propagating disease many months later – the classic 'long tail' of the power law. De Aguiar and Bar-Yam (2005) take the analysis further by modelling the effect of perturbations on the networks. Analysing spectral density, they have shown that the density of states contains information about network topology, and also regarding how external perturbations affect network dynamics. These perturbations are of considerable interest to those studying market failures and financial crashes.

There is not always agreement among researchers looking for common properties across various networks. But some argue that by utilising similar frameworks that mimic network dynamics, universality could be found. For instance, Barzel and Barabasi (2013) have constructed such a model based on two terms: one that develops the property according to the property itself, and second how the property in one node is affected by the properties of neighbouring nodes.

2.4.3 The influence of network centrality

One of the most important measures in network science is the concept of centrality. Centrality is the measure of how central a node is in a given network topology. This can therefore be thought of as which nodes are the most important to a network. This is clearly of huge interest in this project (e.g. the ability to identify the most important people to product development can ensure that the proper resources are extended to them).

There are several well established centrality measures that will be briefly explored. The most basic centrality measure is the 'degree centrality'. Quite simply, it is simply the degree of the node. The most central node being the most connected one (Freeman 1977, 1978). The issue with this centrality measure is that it gives no indication of its ability to connect cliques or of how likely information reaches or propagates from/to the node.

'Closeness centrality' is how central a network is to the network in terms of shortest paths. Therefore, as with the degree centrality it makes no indication of its ability to connect cliques, but it does give an indication of how well information propagates to/from it.

'Betweeness centrality' is a measure of how in-between a node is between two other nodes (Freeman 1977). This is measured by how many times a node is visited when calculating all the shortest paths in between two other nodes. This is a strong measure that provides consistent results in real networks. However, it does put an emphasis on being connected to weakly connected nodes and only weakly being central to the network.

'Eigenvector Centrality' is arguably the most versatile and effective centrality measure and has been used in many different applications, most notably as the Google PageRank algorithm (Page, 1999). The Eigenvector centrality measures the influence that a given node has on the overall network.

2.4.4 Network distributions and 'burstiness'

Researchers are also interested in how changes propagate through networks: is the spread gradual, or punctuated by faster and slower periods? In network dynamics, 'burstiness' is a concept that holds that a given propagation doesn't happen with a smooth distribution, but occurs in powerful and sporadic bursts of activity. Many system-wide dynamics (think the web, social networks, information for financial transactions) are driven by human behaviour and human dynamics, as studied by Barabasi (2005) who has investigated in detail the presence of heavy (very long) tails in human dynamics. Therefore, understanding the drivers of human behaviour is central to many challenges in the embryonic field of network science.

Although some human behaviour models have been predicted by Poisson processes (Haight, 1967), there is now increasing evidence that for communication and work patterns, network dynamics indeed appear to show long periods of inactivity followed by bursts of activity Karsai, M (2012). This is because a Poisson distribution decreases exponentially, which makes each sequential event occur within (relatively) regularly-spaced time intervals. In contrast, in the scale-free networks, a heavy tail that decays slowly can allow for the bursts of activity we see, particularly in communications. This phenomenon is seen empirically by a study that captured the activity of several thousand people using email (Pastor-Satorras, 2001), which found replies in bursts, not with (relatively) equal time in between answers. Similar patterns are seen in financial transactions and online game-playing.

2.4.5 Herding behaviours in financial markets

The term "following the herd" is a popular idiom, say for the popularity and purchase of pop music. But what is herding behaviour in terms of decisions that affect financial markets?
According to Bikhchandani and Sharma (2000), herding can be defined as: "An individual can be said to herd if she would have made an investment without knowing other investors' decisions, but does not make that investment when she finds that others have decided not to do so".

In simple terms, it's about imitating the actions of others: information is revealed when investors take actions, so replicating this action might lead to a profitable investment. This type of copying action can lead to information cascades, which have been defined by Hirshleifer and Teoh (2003) as: "Observational learning in which the observation of others (their actions, payoffs, or even conversation) is so informative that an individual's action does not depend on his own private signal".

In practical terms, this equates to people copying other's behaviour based on public information instead of using private information. A positive cascade can be defined as when open, public information leads to investment decisions. A negative cascade, therefore, when open, public information does not lead to investments (or 'do not invest' decisions) leads to repeated 'do no invest' decisions.

Several microeconomic models of herding describe it as a rational learning process, but where decisions across the herd reinforce each other and are thus interdependent.
We have detailed how herding can be described as a bounded rational response to imperfect information, which then generates convergence towards an outcome determined more by social information and herd actions over private information. Bikhanchandi, Hirshleifer and Welch (1992, 1998) have developed a model which works on this basis, where in sequential decision-making (when each decision conveys no real new information to following members of the herd) informational cascades emerge when it is optimal for an individual to follow the actions of their predecessor instead of their private information. Just as is seen in Banerjee's model In both models,

When private information is frequently disregarded in herding behaviours, occasionally this can lead to stable outcomes, such as no-one buying a new stock. But convergence towards peculiar and unstable outcomes is arguably a more likely occurrence (Chamley 2003)

2.4.6 Basic herding models

Simple information-based herding models (e.g. Banerjee 1992, Bikhchandani et al. 1992, and Welch, 1992), assume that the same identical investment is available to all who would like to invest at the same price, discounting the effects of previous investments, such as price increases as stock becomes rarer.

In these models, investors have the same yes-no binary investment decision and have imperfect, but useful, information on which to base their decision, such as the historical prices of a certain stock. But this information is uncertified: investors can only see the actions of previous investors, not the private information or signal received that led to the investment decision. Herding can occur under these conditions, but it is considered of limited power because one new important bit of information could slow and then stop the herding behaviour.

In models when the investors act sequentially in a predetermined order, the actions of the first few investors are critical in determining whether herding behaviour can arise or not. Let’s say two investors receive information and each acts using conditional probabilities under Bayes’ Law (the probability of an event occurring, based on prior knowledge of conditions related to the event).

It gets interesting when a third investor joins the scene (in this example, let’s say one investor did and one didn’t invest), which is where an information cascade can begin. The third investor will follow the lead of the first tow investors if they do invest, assuming that the first two investors acted on good signals. Subsequent investors will also follow suit, regardless of their own private signals or information, again assuming the previous investments are based on sound knowledge, even though no new ‘real’ information has been received – each subsequent investor is essence still copying the actions of the third investor. This is the positive cascade, and in general a positive cascade occurs if the number of previous participants who invest exceed the number who don’t by two or more.

Similarly, a negative cascade can begin when the first two investors do not invest, and so he or she also does not invest. In this case, subsequent investors do not benefit because they have no new information to act upon, and this decision to follow the previous (in)actions is thus considered rational.

In Bayesian terms, when public information outweighs private signals, the decision to cascade is considered justified. In these models, the addition of new and relevant information can, of course, interrupt the cascade as investors to reassess their beliefs based on new data.

2.4.7 Experiments to test theories of herding

Economic experiments have tested Bayesian theories of rational herding, such as Anderson and Holt (1996, 1997), that confirm Bayesian hypotheses. Some of these experiments have further distinguished herding in general as mimicking behaviours, as opposed to informational cascades that originate from in uncertain scenarios (Sgroi 2003, Çelen and Kariv 2004, Alevy et al. 2007).

For example, Avery and Zemsky (1998) and then Park and Sgroi (2009) allow rational herding and behaviour contrary to herd choices (known as rational contrarianism) in a herding experiment with conditions including multiple states and multiple signals. They find that around 70% of subjects' behaviour is consistent with their benchmark for rationality, and conclude that policymakers should not consider all herding as irrational. Moreover, better information and more accurate signals can lead to decreased herding.

Others have adapted Bayesian models to include flexible prices where information cascades cannot occur, such as Cipriani and Guarino (2005). Their models find that a proportion of subjects do not utilise their private information, instead either not trading or making decisions against the prevailing information (contrarian trading).

2.4.8 More complex herding models

There are models that take account for investors having access to different information. Welch (1992) has modelled the consequences of information cascades on fixed-price IPO sales under such conditions, acting sequentially. In this model, investors gauge interest in an IPO by scrutinising the actions of previous investors. This scenario also leads to cascades when investors mimic earlier investment decisions and ignore private information. This model finds that that initial price is key to kicking off information cascades: too high or too low can lead to oversubscription (positive cascade) to shares or significant lack of investment (negative cascade). It follows that if IPO stock is underpriced, then a positive cascade results as investors flock in to pick up a bargain. By contrast, if stocks are overpriced then a negative cascade occurs as buying remains negligible.

There are models with more realistic starting assumptions. For example, Chari and Kehoe (2004) have developed a model where cascades persist even when information is shared among investors.

Herding behaviour is seen when three conditions are met: 1) continuous rather than one-off binary investment decisions; 2) assets are priced dynamically; 3) investors can invest when they choose, not in an order.

2.4.9 The role of individuals in different herding models

Herds result in herd-like behaviour, but it cannot be ignored that herds are made up of individual people. Individuals are different in the ways that they rationalise and apply statistical data, as reported by Salop 1987; Baddeley et al. 2005). These differences in cognitive competence with regard to the use of statistics, for example, may result in 'reverse cascades', which are when 'incorrect' decisions send information cascades the 'wrong' way, away from prevailing expectations (Sgroi 2003). These considerations predict that if herding results from individuals saving time (and cognitive effort, it could be argued) and resorting to practical heuristic decisions, then specific personality types will be more likely to use these practical measures to shortcut difficult decisions. It is in essence the overriding application of common sense in certain situations, known as 'procedural rationality' (Baddeley 2006).

2.4.10 The crowd and herd behaviour

Economists have started incorporating investor psychology into finance over the last two decades to try and explain unexpected or unpredictable data regarding fundamental financial theories like the efficient-market hypothesis (EMH), or the capital asset pricing model (CAPM) first introduced by was introduced by Jack Treynor over 1961-62. The field of behavioural finance assumes that, to some extent, all investors are irrational. This assumption about investors' irrationality can account for certain financial observations, such as overreactions to information, seasonal stock price effects and herding amongst investors.

The reasons for rational behaviour have been detailed by Barberis and Thaler (2003), who give a two definitions of investor rationality: 1) agents update their beliefs correctly when they receive new information, in the manner described by Bayes' theorem; 2) given their beliefs, agents make choices that are normatively acceptable (notably, the use of Bayes' theorem, which is the probability of an event based on prior knowledge of related conditions. Providing up-to-date information on investors' beliefs is central in other herding models, such as those of Scharfstein and Stein (1990), Banerjee (1992), Bikhchandani et al. (1992) and Welch (1992).

Others think that people are generally bad at determining probabilities accurately, as detailed by Fischhoff et al. (1977), for example. They report that overconfidence can lead people to predict an occurrence with 100% certainty when the actual probability is, say, only 80%. Similarly, Barber and Odean (1999) say investor overconfidence causes over-trading and can lead to significant losses, as can over- and under-reaction to good and bad financial news as Barbaris et al. (1998) and Daniel et al. (1998) have explained.

Overconfidence can also affect not just individual investors, but the economy as a whole. Lo (2002) suggests there is a correlation between optimism/pessimism in wider society and financial market conditions; specifically that a feeling of optimism in society translates to more optimistic investors, and hence more optimistic but riskier investments due also to the underestimation of relevant risks, as highlighted by Fischhoff et al. (1977) and Barber and Odean (1999).

2.4.11 Crowds and information cascades

Information can multiply through groups of people in a phenomenon known as 'information cascades'. Bernardo and Welch (2001) discuss how the actions of a clique of overconfident investors can change the decisions and outcomes of the actions of a larger group of investors. When too much emphasis is put on private information, the total amount of information aggregation amongst the group increases. This is due to investors placing less emphasis on the actions of the herd and an overreliance on their private information: the result is that they end up broadcasting this 'private' information to the rest of the group, who then make irrational choices. Anderson and Holt (1996) have demonstrated these information cascades in a laboratory setting.

Another phenomenon is also at play here is when a person forms an opinion and sticks to their guns for too long, named 'belief perseverance' by Lord et al. (1979). They note that people don't want to find or see evidence that contradicts their opinion – who wants to be wrong? – and when presented with evidence contrary to their beliefs, it is seen with scepticism. The result is that investors involved in a positive information cascade hold onto the thinking that the previous investors' decision to invest suggests that they should do the same and the positive cascade continues.

Finally, it is established that people follow people, but people will also follow computer-generated decisions. Intriguingly, this suggests that following the herd is not just a facet or aspect of peer pressure or other social influences (Bikhchandani et al. 1992).

Herding behaviour is, therefore, the summary of a complex interplay between the rational and the cognitive, the emotional and instinctive all played out against a backdrop of psychological, sociological and economic and even technological factors. In the last chapter of this thesis, we introduce a model of herding and emotional cascad

Chapter 3 Market Risk Profiling

3.1 Summary—in a number of consulting sectors 'designing for uncertainty' is a core competency and the design of system models is a primary service offering. This is particularly true in financial risk consultancy and engineering crowd flow management where a client commissions the development of a bespoke model and a report on the model's output. The aim of this chapter is to critically review approaches to 'designing for uncertainty' in financial risk management and Engineering crowd flow Management. This chapter contributes to knowledge by performing a systematic literature review of papers in ScienceDirect on the topic of 'designing for uncertainty' in the crowd flow consulting and comparing it with findings from the financial risk sector. This survey identifies three key sources of uncertainty to be managed during the design of system models: parametric; structural; and method uncertainty. Best practices for managing each of these types of uncertainty are identified from existing practices in the crowd flow and financial risk management sectors. We identify opportunities for learning across the disciplines and conclude that further research is required to refine techniques for designing for uncertainty during the system model design process.

3.2 Introduction

In a number of consulting sectors 'designing for uncertainty' is a core competency and the design of 'system models' is a primary service offering. This is particularly true in financial risk consultancy and crowd flow consulting where a client commissions the development of a bespoke model and a report on the model's output. The uncertain nature of crowd flow systems and financial systems presents a design challenge for these industries. This is because they are required to design models for situations where there is considerable uncertainty concerning the inputs, interacting parts or outputs and yet the models they produce need to be robust enough to inform safety critical or business critical decisions.

The aim of this chapter is to critically review approaches to 'designing for uncertainty' in financial risk management and Engineering crowd flow Management. It should be noted that neither discipline uses the term 'design for uncertainty' so this paper aims to bring together existing system model design practices related to uncertainty and thus provide a starting point for the development of a coherent set of 'design for uncertainty' practices.

This section identifies good practices, discusses their strengths and weaknesses, and identifies opportunities for cross-disciplinary learning / further avenues for developing 'design for uncertainty' practices within the context of designing system models. In section 3.3-3.6 the reader is introduced to important definitions and concepts such as system model design, uncertainty and the notion of 'designing for uncertainty'. In section 3.7-3.8 the literature survey methodology is described and the findings are presented and critically analysed. In section 3.9-3.10 opportunities for cross-disciplinary learning are identified and gaps within the literature discussed.

3.3 Background

System Model Design

In this chapter *design* is defined as both the content of a set of plans and the process by which those plans are produced [1]. *System model design* is defined as the process that transforms requirements and information about a system of interest (inputs) into specifications and blueprints (outputs) of a model that will meet a client's requirements.

The practice of system model design can be described as artisanal and thus require a highly skilled practitioner. There are no mechanistic design processes by which robust system models are developed, engineering guidelines or explicit design patterns. The practice of system model design is generally reliant on an individual practitioner experience, judgement and expertise.

The type of system model design that typically occurs in the financial risk management and crowd flow sectors can be classified as the adaptive design [2]. Established solution principles are adapted to meet a client's bespoke requirements. This normally entails using, customising and combining techniques and modelling components to provide a model that informs safety critical or business critical decisions despite the uncertainty present.

The practice of system model design is often iterative and exploratory due to the uncertain nature of the systems being modelled. An informal process resembling the ‘Spiral model’ [3] can be seen to tacitly followed by practitioners. A number of prototypes are typically developed in an iterative manner. Each prototype explores an area of concern/uncertainty until the modelling team is satisfied that the final model will be informative despite the uncertainty present.

Each iteration typically comprises identifying design objectives and constraints, identifying design alternatives, identifying and resolving risks from the selected design alternative. Risks are usually resolved by means of prototype development/data collection and progress evaluation. The cycle is repeated until an informative model is developed or that it is concluded that at present an informative model cannot be developed.

Uncertainty

Uncertainty is used in two distinct senses reflecting distinct and contrasting usages of the term in finance and the simulation sciences. In finance, uncertainty (Knightian uncertainty [4]) refers to situations where a person is uncertain about how uncertain they are. This is exemplified by a roulette wheel with an unknown set of numbers inscribed - it is thus impossible for a person to attribute a probability to any particular outcome since it is impossible to enumerate the possible outcomes let alone how frequently one might expect them.

Uncertainty is also used in a second distinct sense as per simulation science, where it refers to situations where you are certain about how uncertain you are – in finance this is often referred to as ‘risk’. For example, given a fair European roulette wheel, you know it can output an integer between 0-36, you know each outcome is equally likely, so although you are uncertain of the outcome of the next spin you are certain of the likelihood of the outcome.

This second notion of uncertainty is particularly important in the modelling and simulation sciences because information about a system’s input parameters, structure and outputs are often known to be uncertain due to data scarcity/quality issues/non-determinism yet it is certain that the true value lies within a range and so the likelihood of the value can be expressed mathematically. These three types of uncertainty present in models are commonly referred to as:

- parameter uncertainty;
- structural uncertainty;
- method uncertainty.

Parameter uncertainty refers to situations where there is uncertainty about the values of the inputs or outputs of a system to be modelled [5]. Parameter uncertainty poses a challenge because calibrating a model to uncertain system inputs or outputs leads to uncertainty about the appropriate model calibration values.

Structural uncertainty refers to situations where there is uncertainty about the components of the system to be modelled [5]. Structural uncertainty poses a challenge because there may be multiple candidate model structures each representing different interactions or parts. A modeller needs some way of deciding which model structure is most informative for the decision-maker. In some situations, the uncertainty may so great that the structure is deemed uncertain (in the Knightian sense) and so a purely statistical 'black box' model is developed – this is a common practice in financial risk management where financial systems can be vast and highly coupled.

Method uncertainty refers to uncertainty about the appropriate modelling techniques [5]. Method uncertainty poses a challenge because different modelling approaches (such as System Dynamics [6], Agent-based Modelling [7], Queuing Theory [8], and Continuous Time Modelling) provide different formalisms for representing a system and thus provide differing capabilities for expressing system structures. If a modeller selects an inappropriate method then the model will not be capable of expressing the desired structure and thus reproducing behaviour representative of the system.

In all three of the above uncertainty situations, models can be designed and developed despite the uncertainty present because it can be the case that a model is sufficiently insensitive to the level of uncertainty present resulting in informative model outputs.

3.4 Uncertainty in Crowd Flow Modelling

In crowd flow modelling, agent-based models (ABMs) [7] are frequently designed and developed to represent a people flow system of interest. ABMs usually represent each person as an agent with defined properties and behaviours (such as height, width, body weight, walking speed, rate of acceleration …) and a built environment (comprising rooms, corridors, stairs, lifts, roads, pavements, trees, and outdoor furniture). The simulation is then processed to generate information to inform a client's decision.

Unsurprisingly there are multiple sources of uncertainty in ABMs that a simulation output can be sensitive to. These include any of the above-mentioned agent parameters, the placement of elements in the built environment. There are of course also structural uncertainties such as the rules that govern the interactions between agents such as those that determine desired levels of personal space, route choice and the attractiveness of certain locations [9]. More generally there can be method uncertainties such as whether an ABM is an appropriate method for representing the system rather than cellular automata or a queuing model.

Due to this wealth of uncertainty, crowd flow models need to be 'designed for uncertainty'. This is because a model outputting a definitive value (rather than providing a distribution of values and their likelihood) is uninformative to a decision-maker as its sensitivity to the uncertainty is unknown.

It should be noted that designing people flow system models for uncertainty is a significant challenge since it requires careful and iterative requirements gathering, analysis, concept development, detailed design, implementation, validation, and verification.

3.5 Uncertainty in Financial Risk Modelling

In financial risk modelling, models are designed to enable decisions to be made in the presence of uncertainty. With increasing reliance on numerical models and simulation codes for predicting the behaviour of complex financial systems this is a particularly pressing challenge. i.e. Models have used predict asset prices, forecast market movements, and inform portfolio optimisation decisions.

Due to the nature of financial markets, models are usually stochastic and continuous in nature, thus require complex algorithms, involving computer simulation, sophisticated numerical methods and/or the development of optimization models. A key difficulty in optimization under uncertainty is in dealing with an uncertainty space that is huge and would lead to very large-scale optimisation models that are often unachievable in practice. Designing for uncertainty is often further complicated by the presence of subjective decision variables and decisions in a multi-period or multi-stage setting.

When designing a financial model for actual industry use, the designer should have the ability to test model assumptions in order to analyse the impact on future financial performance. The performance of a model is often judged by comparing the outcomes derived from the model with the observations made at future date.

The designer must also manage uncertainty in quantifying both input data and output response. Errors and approximations in a model also affect the deviation of the model predictions. Verification and validation under uncertainty thus involve measuring the error in a model's prediction despite the stochasticity present in both the prediction and the empirical test data.

Sensitivity analyses are used to model the effect of changes in input variables for some input of interest, such as interest rate or GDP growth. It is often helpful to build a series of sensitivity analyses to get a sense for what input uncertainty will have a significant influence on your output measure or metric of interest i.e. stock market return.

3.6 Designing for Uncertainty

The phrase 'designing for uncertainty' is intended to capture the challenge that system models need to be designed to inform safety critical or business critical decisions despite considerable uncertainty concerning the inputs, interacting parts or outputs. In practice, this is operationalized as the design of system models that produce the likelihood of a set outcomes given a set of parametric, structural and method uncertainties.

On first impression, this may not sound like a design challenge but merely a matter of 'number crunching'. This is not the case because the parameter space of crowd flow and financial risk models is potentially vast. They do not typically lend themselves to analytic solutions (without gross assumptions) and the systems they represent are usually stochastic in nature. This means that the model designer must manage the constraints of a limited amount of:

computational power;

time;

information;

with the need to produce a model that is sufficiently uncertainty insensitive to be useful to a decision-maker. This management of practical constraints is similar to the design of any artefact where size, weight, performance, cost, schedule and quality trade-offs need to be made.

In practice this means that system model development is a highly iterative learning exercise where the practitioner is continuously learning/evaluating:

how sensitive their model is to uncertainty?

how computationally expensive it is to run?

whether the model outputs are informative?

This means the practitioner requires a set of techniques for identifying the uncertainties present and analysing their model's sensitivity to these uncertainties with respect to the information a client is seeking to gain. In the following sections, we will review the strategies used in crowd flow Management and financial risk modelling to manage the uncertainty present in this design challenge.

3.7 Survey of Design for Uncertainty practices in Crowd Flow Management and Financial Risk Management

A systematic literature review was performed to identify articles for review.

By analysing these papers we were able to identify the following approaches as candidate best practices for managing each kind of uncertainty during the design process – see Table 2.

CROWD FLOW – CANDIDATE BEST PRACTICES

Type	Candidate Best Practices
Parametric Uncertainty	Uncertainty methods: • General Uncertainty and Sensitivity Analysis [10] • Bayesian Sensitivity Analysis [11-13] Emulation: • Support Vector Regression [10] • Gaussian Process model [13, 14]
Structural Uncertainty	• Portfolio of models approach [5, 15] • Expert judgment approach [16]
Method Uncertainty	• Multi-methodology [5]

We were also able to identify potential gaps / further areas for exploration in the crowd modelling literature due to a lack of work with respect to structural uncertainty and method uncertainty.

We believe that key areas for further work are:

1. Development of case studies applying global uncertainty and sensitivity analysis to crowd flow system models to give practitioners a better understanding of which parameters are the most important to invest effort in calibrating and exploring during the design process;

2. Exploration of the use of emulation/surrogate models in crowd flow ABMs to understand their potential contribution to system design in terms of increasing the computational tractability of crowd flow system models and thus reducing the time spent analysing each model iteration.

3. Development of case studies that apply methods of structural uncertainty analysis and method uncertainty analysis to crowd flow model design. At present, there is little guidance to

practitioners as to what methods are appropriate to apply during the design of models of different types of crowd flow systems and usage scenarios.

Managing Parametric Uncertainty in ABMs

Our survey identified three approaches for analysing parametric uncertainty in agent-based models. These were:

1. One-factor-at-a-time (OAT) approaches
2. Global uncertainty analysis approaches
3. Bayesian uncertainty analysis approaches.

OAT approaches are those that assess the impact of parameter uncertainty by varying a single parameter at a time and identifying the impact of the parameter on a set of outputs [17]. OAT approaches are known to be limited with respect to ABMs because they assume linearity between inputs and outputs however ABMs can be highly non-linear thus making the approach unsuitable. Instead of simply using OAT it is generally recommended that practitioners explore the linearity of the models using a factorial design and explore linearity using a regression analysis [17]. In non-linear cases, global uncertainty analysis approaches are far more suitable however they known to be more expensive in terms of computational time [10, 18].

Global uncertainty analysis approaches are those that sample a multi-dimensional parameter space to assess the impact of parameter uncertainty on a set of parameter outputs [10, 17]. These approaches are designed to cope with non-linear interactions between inputs/outputs and thus provide a thorough analysis of parameter uncertainty in an ABM. A well-known disadvantage of these approaches is that they are computationally expensive because they require a large number of samples (executions of a simulation) to produce meaningful results. This can make them prohibitively expensive because ABM models may take hours or even days to execute a single-run depending on the model. To make global uncertainty analysis suitable for ABM a technique called emulation is often employed.

Emulation comprises creating a computationally less expensive approximation of an ABM for the purposes of performing global uncertainty analysis. Our survey identified two promising approaches for emulating agent-based models. The first approach, support vector regression SVR [10], approximates the ABM using machine-learning algorithms and a training dataset to generate a function that approximates the output within an acceptable error margin. This approach is particularly promising because it is applicable to systems that have non-monotonic outputs.

The second promising approach for emulating agent-based models is the Gaussian Process Model (GPM) [13, 14]. Gaussian process models are used to build an approximation of a function from a training dataset. The benefits of GPM are that it is extremely fast to execute and it also accounts for uncertainty within the outputs it produces. Furthermore, the Gaussian distribution is straightforward to analyse and therefore derive various uncertainty and sensitivity analysis measures analytically. GPM is more limited that SVR however because it assumes that the output of the function it is approximating is a smooth function and therefore may be viewed as a means of smoothly interpolating the training set to emulate the ABM.

Bayesian uncertainty analysis approaches are those that adopt a Bayesian rather than Frequentist view of probability. A Bayesian approach treats model parameters as random variables derived from a particular distribution [11-13][3]. The benefits of a Bayesian approach is that prior information about a parameter can be input into a model (e.g. a parameter's distribution) and its impact on the distribution of model outputs can be generated. Another benefit is that Bayesian approaches can reduce the number of simulation runs required to estimate uncertainty by making use of information between points in a parameter space to more effectively choose samples of the parameter space and reduce sampling by 2-3 orders of magnitude in comparison to Monte Carlo approaches [13].

The Bayesian approach also enables an analyst to ask questions such as the probability of an output exceeding a threshold value[4]. It can be argued that in complex and uncertain decision-making situations it can be more useful to know a parameter's distribution and thus the probability of an output exceeding a threshold rather than a simple true/false with a level of certainty.

All the approaches above are techniques for 'designing for uncertainty' as they help a practitioner evaluate the viability of candidate designs to be sufficiently insensitive to parametric uncertainty to be informative. This information acquired then feeds into the next iteration suggesting that where design effort needs to be invested.

[3] In contrast frequentists treat parameters as fixed quantities i.e. they assume that if a parameter is measured a large enough number of times the variation in its mean value tends to 0 and so it becomes a fixed quantity.

[4] This contrasts with frequentist approaches that will test whether the true value is above or below a threshold value.

Managing Structural Uncertainty in ABMs

Our survey identified two approaches for managing structural uncertainty. These were:

1. Portfolio of models
2. Expert judgement

The *portfolio of models* approach comprises analysing structural uncertainty by modelling the same system using different model structures and comparing the differences in simulation output. This enables the modeler to bound the effect of opting for one model structure vs. another model structure. This approach was used in [5, 15]. The benefit of this approach is that it enables the quantification of the effect of using different model structures. The drawback of this approach is that it is computationally expensive because sensitivity analysis needs to be performed on multiple model structures. The expense can typically be reduced by using emulation to approximate models and therefore make structural uncertainty analysis computationally tractable. Another approach is to use a goodness-of-fit function to identify a single model and then perform an uncertainty analysis on the single model [9].

The *expert judgment approach* comprises asking experts to estimate the uncertainty introduced by a particular model structure. A typical approach such as that of [16] suggests a five-step process.

1. Identify all potential differences between the simulation model and reality
2. Assess the size and probability of each difference
3. Assess the sensitivity of simulation results for changes in parameter values
4. Assess the effect of each difference on the outputs of importance
5. Determine the joint effects of all differences.

The benefit of this process is that a systematic assessment of all potential sources of uncertainty is undertaken (including structural uncertainty) and the effect of this uncertainty is taken into account when understanding the policy implications of simulation outputs. The drawback of this approach is that it is labor intensive and relies on a depth of human expertise to assess the size and probability of each difference.

All the approaches above are techniques for 'designing for uncertainty' as they help a practitioner evaluate the viability of candidate designs to be sufficiently insensitive to structural uncertainty to be informative to decision-makers. If there is little difference between the uncertainty introduced by two structures then the most computationally tractable structure can be selected and the computational run-time or design effort can be dedicated to a different part of the system model. If there is a significant difference then the design team can invest time gathering data to reduce uncertainty about which structure is the most appropriate.

Managing Method Uncertainty in ABMs

Multi-methodology is proposed in [5] as a method of exploring method uncertainty in modelling and simulation. Multi-methodology consists of using multiple modelling methods to model the same system and then assessing the differences in model output to triangulate method uncertainty. This enables a form of triangulation such that similar results are generated by models based on different assumptions or paradigms.

The drawback of this approach is that it can often be impractical to develop multiple models of the same system using contrasting modelling approaches. Limitations such as lack of time, budget, expertise, and manpower typically limit its use in non-trivial situations where a simple mathematical model will provide a reasonable approximation of the agent-based model and thus will act as a means of sense-checking the ABM.

Multi-methodology is an important design for uncertainty technique as it enables the modeller to gain assurance that the tacit assumptions of their modelling methods are not distorting model outputs in any material way. This can be particularly invaluable in design situations where real-world data in unavailable because the model is to forecast into the future or explores system behaviours that are too dangerous/expensive to create.

3.8 Financial Risk Modelling

In contrast to modelling physical systems, when modelling financial markets, there are many different market participants that impact price level by their trade decisions. Hence, a model trying to apprehend the whole market microstructure with all exchanges of market participants would be colossal and extremely complicated attempt with loads of parameters, such an approach is only manageable under severe simplifications. But, additionally, there are few other reasons not to model the microstructure of financial markets.

1) Financial markets cannot be put under laboratory/experimental conditions and therefore models cannot be tested for reliably.

2) Complexity in the operations makes it impossible to observe all market participants' behaviour and their relationships simultaneously.

3) Many market players display irrational behaviour which may be difficult to model even when modelling only a single individual participant.

(There have been approaches in behavioural finance trying to provide a scope for such a kind of behaviour as in “Prospect Theory” [19], but research on that area is which still on-going.)

4) The financial market system is dynamic, with new market players entering and leaving the system. Even if one could observe the market players’ behaviour and collect huge amounts of data, in every second, new market participants enter the financial markets and behave differently, such that predictions relying on historical data might not explain future market situations successfully.

Montier [20] even argues that relying too much on collected data may result in overconfidence, since the data may not be representative anymore to model future events.

Hence, the typical approach to model financial markets is to ignore the market microstructure i.e forgetting about the market player’s action/interaction and to model asset prices statistically. One should note that there are some approaches trying to capture the microstructure with limited success.

we were able to identify the following approaches as candidate best practices for managing each kind of uncertainty during the design process – see Table 3.

FINANCIAL RISK MODELLING – CANDIDATE BEST PRACTICES

Type	Candidate Best Practices
Parametric Uncertainty	Uncertainty methods: • Paramters input of black scholes model of option pricing • Bayesian updating process paramter estimation [24] [25] [26] [27]
Structural Uncertainty	• stylized facts of financial returns [21] • black and litterman global portfolio optimization (Expert judgemen required)
Method Uncertainty	• Expected utility Hypothesis, Risk Aversion [28] [29] [31] • prospect theory [19]

Type	Candidate Best Practices
	• Traditional finance vs Behavioural finance

We were also able to identify potential gaps / further areas for exploration in the financial modelling literature due to a lack of work with respect to parameter uncertainty.

We believe that key areas for further work are:

1) Conducting a survey on the main financial models i.e Capital asset pricing model, Markowitz Portfolio optimisation, Option Pricing, Real Options, arbitrage pricing theory and corporate finance models

These models play a central role in the financial world and they are often stochastic in nature containing single or multiple parameter inputs and exposed to structural and method uncertainty.

2) Apply uncertainty budget cost to the financial models above, Effective uncertainty budgeting and forecasting are vital components of sound risk management and provide an accurate forecast of anticipated revenues and a roadmap for appropriate asset allocation.

Managing Parametric Uncertainty in Financial Risk Models

To set up a reasonable stochastic model for asset prices, one typically analyses stylized facts of the time series of the asset price process and tries to imitate these properties with stochastic models fulfilling as many of these stylized facts as possible [21].

Compared to an ansatz focusing more on data (an extreme ansatz may be a non-parametric one only exploiting data), such a modelling paradigm allows the capturing of general movements. Furthermore, a stochastic model of a stock price should be tractable enough in the sense that it costs moderate effort to simulate the stock price and prices of related financial instruments (e.g. forward and swaps) may be calculated in an analytic technique. With these requirements for a model, one starts to collect some stylized facts of time series of asset prices and obtains as first observations:

First: The distribution of returns is approximately symmetric and has high second and third moment i.e kurtosis, fat tails and a peaked center compared with the Gaussian distribution. Second, the autocorrelations of returns are all low and close to zero. Third, the autocorrelations of both absolute returns and squared returns are positive for many lags and they imply considerably more linear dependence than the autocorrelations of returns.

Selecting the second stylized fact as a starting point, a possible tool for modelling stock returns seems to be the normal distribution, which is widely understood, mathematically tractable and plays a well-known role in asymptotic statistics (due to the central limit theorem).

When developing a stochastic model, one often observes a complicated state where the outcome in concern behaves in a more or less unpredictable manner. In some cases, a simple and accurate description may be provided easily. But, typically, the object to model is much more complicated (i.e option pricing model). Hence, it is not clear from the beginning that the choice of one stochastic model is a good choice or a different model might be more suitable, like choosing either a Black–Scholes [ref] or a jump diffusion [ref] for stock prices.

Usually, the quantity of interest is modelled by a random variable S or some stochastic process. Hence, a situation where modelling may be complex can be mathematically described as a situation where a whole set of probability measures -which may typically be infinite- is available for modelling. Sometimes, the set of possible probability measures (i.e. different stochastic models) may be parameterized in an official way by a parameter space Θ, i.e. $S = (S\theta: \theta \in \Theta)$.

The influential dissertation of Knight [4] analyses the situation where different states S1, . . . , SN are possible outcomes for X. a distinguishes between two possible states that may occur:

First one knows the probability of each possible outcome S1,,,,,,,,,,,,,,,,, SN.

The 2nd situation, where hardly any information is presented, is called uncertainty by Knight [4]. The 1st situation which allows for a probabilistic description is known as risk.

Obviously, facing risk is a distinctive case of uncertainty -since one could always forget about the probabilities - and a more comfortable situation compared to facing real uncertainty. One can try to deal with a risky situation by risk management, i.e. using the information about the probabilities of the different outcomes and acting such that a specific risk function is minimized.

Examples Parameter uncertainty in financial market models

All Financial models are exposed to parameter uncertainty. We will discuss here one of the most widely used classes of financial models used to price options contracts. These models use parameters some of them are given and other experience true parameter uncertainty in the sense that no information about the parameters is known.

1. Looking at the Black-Sholes (BS) model of asset prices, where the stock prices follow a stochastic differential equation governed by Brownian motion, taking into account interest rate and stock volatility.

$$dS_t = rS_t dt + \sigma S_t dW_t, \quad S_O > 0,$$

Where St is the initial stock price and r is the risk-free rate which is available from the market, one does not have direct information about the volatility. Hence, a priori every positive number σ> 0 can be chosen. Usually, one uses market data to calculate volatility from a time series of stock prices or fits the model to the prices of traded instruments to quantify the volatility.

2. Heston model, the stock price dynamics follow the coupled stochastic differential equation

$$dS_t = rS_t dt + \sigma_t S_t dW_t^{(1)}, \quad S_O > 0,$$

$$d\sigma_t^2 = k(\sigma_t^2 - \sigma_{long}^2)dt + \xi \sigma_t dW_t^{(2)}, \quad \sigma_0^2 > 0,$$

Contrary to the Black–Scholes model, the number of unknown parameters is higher. Again, as in the Black-Sholes model, the initial stock price is S_t and the risk-free rate is r both known by market quotation. On the other hand, the initial volatility σ_0, the mean reversion speed k > 0, the long-term volatility σ^2 >0, the volatility-of-volatility ζ > 0, Hence we face parameter risk concerning the parameters σ_o, k, σ^2, ζ .

Even across different models and when establishing complete fits to market prices of standard instruments i.e. American or European call options, one finds that there is still ambiguity and different models may cause different prices for non-standard options [22].

Managing Structural Uncertainty in Financial Risk Models

Shifting the concepts of risk and uncertainty to stochastic modelling, in a state of having a whole set of models P to choose from for modelling is commonly stated as model uncertainty. If each model can be identified by a parameter θ from some parameter space ϴ, one speaks about parameter uncertainty.

From a purely mathematical point of view, distinguishing between model and parameter uncertainty is just up to a mapping ϴ→ P which may always be obtained for some set θ. often, the set θ can be chosen such that considering different parameters θ ϵ ϴ allows for more appropriate interpretation in the real world than treating the corresponding model Pθ.

If we additionally have given a probability measure K on the set of possible models P which quantifies the probability of each model to be the right pick, then we are in a setting of model risk, which can be considered as a specific case of Structure uncertainty

Model and parameter uncertainty arise in numerous situations. If one faces a complex situation where a stochastic model is used, one is often uncertain between different models to choose from. Even after having decided for a particular parametric model, the correct determination of the model's parameters is not straightforward and may result in different difficulties.

When stochastically modelling financial objects, there are a large number of possibilities to simplify, thus many different models are competing with each other. In option pricing, model risk should not be underestimated [23]. During the Credit crunch and financial crisis 2008, where massive misevaluation of portfolio credit default swap instruments played an important role.

A popular mathematical tool, when faced with model risk, is Bayesian statistics. The basic concept behind Bayesian statistics is that the association between distributions of different models and samples thereof is not static, but is a dynamic process where the knowledge of the model distribution is constantly updated. In this case, it is regarded to be random as well. Hence, one of the key results of Bayesian statistics is how the model distribution is updated and learns from the collected samples. Summarising, the Bayesian methodology is about how to obtain a proper distribution of the models including information about the data into the construction process [24].

A two common application of the Bayesian updating process is when the input source:

First, one has real data on hand for estimating parameters. A classical statistic hypothesis would now solely rely on the given data, estimating the parameters, quantifying descriptive statistics and asymptotic distribution by using theory from mathematical statistics or resampling methods. But, in some cases, one wants to incorporate some specialist opinion as well, particularly in case that the data may be difficult to judge.

The second case where one would like to incorporate specialist opinions is when only very few data is available or a large fraction of data is out-dated. I.e. a future trader might impose a distribution on the parameters of a financial market model being subject to parameter risk. Applying a Bayesian updating process, one would use this distribution being the result of specialist view as the a priori distribution. As a second step, one may use the Bayesian updating procedure and samples from financial market data to adjust the expert view to real-world data.

Example 1: Black–Litterman portfolio selection

A popular application of Bayesian updating is the Black–Litterman model in portfolio optimization [25].

In classical mean-variance portfolio optimization, risk and return characteristics of different investments are simply estimated from historic time series data. A clear weakness of this procedure is that the used data is backward-looking and does not have predictive power about future performance. Hence, one would like to introduce some technique where data is one input, but on the other hand, some subjective analyst opinion may affect the output.

One way to incorporate "analyst market view" into Markowitz optimisation is to use a Bayesian approach. In this way, both subjective opinion in the investment performance and it is associated risk is described in the prior distribution, as well as Historic financial market data can be incorporated by means of Bayesian updating. Consequently, one obtains a new distribution for risks and returns which is used for portfolio optimisation purposes, the method outlined above is called Black–Litterman portfolio optimisation [25].

Example 2 : Bayesian option pricing

The use of Bayesian statistics provide a framework to extract distribution on parameters i.e Option prices can be combined with analyst view to give the most likely outcome. Option pricing is state where one is baring both Parameter and model risk, option pricing is a state where one is exposed to parameter risk and model risk), Therefore, [26] propose to calculate the posterior distribution using Bayesian updating containing new forward-looking data like observations from time series and prices of European Call/Put options.

They also suggested that Call and Put option prices support a true model that is noised by independent Gaussian error terms. A mathematical framework is suggested how this assumption can be interpreted in terms of a parameter prior distribution. In particular, a local volatility framework is used and it is assumed that in the short run, the market implied Black-Scholes volatilities of the most common options are concise approximations for the local volatility.

An interesting point in choosing the prior distribution, once having done the Bayesian updating procedure several times, one may use the old observed posterior density as the new prior to starting with as described before.

In insurance Industry, we are dealing with time series with stationary conditions- observe a stationary behaviour as financial markets – for example, flood claim or insurance loss due to fire. Many textbooks as [27] address Bayesian methods for risk management in insurance and finance field.

Managing Method Uncertainty in Financial Risk Models

Research from finance, economics, and also from behavioural sciences like psychology and cognitive science, has shown that most people display a version for both risk and uncertainty often incorporated under the term risk aversion [28]. A mathematical concept covering risk aversion i.e preferring situations of certainty over situations of risk is described by the foundations of utility theory [29] and furthermore by the introduction of the axioms of subjective expected utility [30]. Arrow [28] and Pratt [31] analyse risk aversion from an economic perspective. Concerning uncertainty, it has been shown that the concept of uncertainty aversion is available, describing that a situation of risk is generally preferred to a situation where true uncertainty is exhibited. Theories attempt to incorporate a wide range of behavioural uncertainty, from the propensity of individuals to be overconfident about their decisions, to a reliance on blatantly irrelevant information, through to a penchant for guidance from superstition or even magic.

Many analysts in the world of finance go so far as to argue that a significant proportion of market participants are completely irrational, at least for some intervals of time. This need not mean that behaviour is beyond explanation, however it does suggest that some events are difficult to evaluate successfully with conventional tools of traditional finance. Psychological theories of the sort are typically invoked to rationalise aberrant behaviour, extreme price fluctuations or extraordinary incidents, rather than as expressions of normal behaviour. Arguably, the theories demand a more central position in finance than they have accomplished. While undermining the pre-eminence of the Expected utility hypothesis, as yet, however, they have not displaced it.

Designing a financial model should take into account these conflicting ideas while the majority of the current financial models are designed under the assumption efficient market hypothesis/ traditional finance, An attempts have been made to overcome the inadequacies of these methods, mainly by appeals to behavioural theories of choice under uncertainty

that are more usually found in psychology than economics. Important though the alternatives are, their appearance has not yet served to oust the more traditional models.

3.9 Opportunities For Cross Disciplinary Learning

There are a number opportunities for cross-disciplinary learning between the crowd flow consulting and financial risk management sectors. These opportunities for cross-disciplinary learning are afforded due to the disciplines similarities in terms of the systems that they are modelling:

Non-linear stochastic systems;

Their system models are subject to parameter, structural and method uncertainty;

The purpose of their system models is to inform decisions that are high-stakes e.g. business critical / safety critical.

It should be noted however that there are some important differences between the disciplines that limit the extent of cross-disciplinary learning. The most notable of these is that crowd flow systems are amenable to micro-level simulation to generate accurate macro-level outputs. Whether this is achievable in the financial markets is an on-going research question and so current industry practice is to use stochastic macro-level models.

Learning Opportunities for Crowd Flow System Model Designers

Crowd flow Management has the following key opportunities to learn from the financial risk modelling sectors. Firstly the financial risk modelling (FRM) sectors provide examples of how to design system models that put monetary values on uncertainty present in a system model – see for example the Value at Risk model [21]. It would be useful in crowd flow Management to be able to understand the financial cost of the uncertainty present in a model and thus enable designers and decision-makers to understand when it is worth investing additional effort in reducing the uncertainty of a model.

Another opportunity for learning is the recognition that a macro-level model capturing a stylised fact can be sufficient for producing an output with the desired level of uncertainty. At present, there is a tendency to use higher fidelity, but computationally more expensive, micro-level models such as the social forces model. Work that attempts to quantify the uncertainties of these different models should be performed so that model designers have a better understanding the trade-offs that they are making.

Another opportunity for learning is the recognition that the FRM sectors may provide examples of how system models can be designed to capture method uncertainty using expert judgements. The Black-Litterman model [25] of asset portfolio allocation provides an example how such a model can be designed.

Learning Opportunities for Financial Risk System Model Designers

Global uncertainty analysis to assess parameter risk is not wildly used in finance as the financial system is complex and dynamic, with new market players entering and leaving the system at all time. That method is computationally expensive and takes hours or even days to execute a single run, so it could have potential in the insurance industry and Pension funds management where they allocate their portfolios of the asset on very long term base, usually 3-6 months.

Emulating agent-based models where Gaussian process models are used to build an approximation of a function from a training dataset, it has been widely used in finance but the Gaussian approximation has come under huge criticism as a model basis for calculating risk and uncertainty in finance recently.

One-factor-at-a-time (OAT) approaches to assess parameter uncertainty is widely used in finance as in VAR analysis, vector autoregression provides one way to estimate the impact of uncertainty on activity. A VAR model is a system of equations where every variable is dependent on its own past values and the past values of every other variable in the system. So an advantage of this method is that it allows uncertainty and target forecast output to depend on one another. And it is possible to introduce an exogenous shock to the uncertainty equation, then observe how that affects other variables within the system. That process is usually accompanied by applying Principle component analysis in such a way that to defined the principal components that have the largest possible variance.

Expert judgement approach to evaluating structural uncertainty is very close approach to evaluate uncertainty in the system as in Black-Litterman model for portfolio asset allocation where experience finance practitioner has to assess the size and probability of each difference sceneries

Portfolio of models approaches to assess Risk and uncertainty is widely used in finance as in Monte Carlo simulations, a way of solving probabilistic problems by numerically 'imagining' many possible scenarios or games so as to calculate statistical properties such as expectations, variances or probabilities of certain outcomes. In finance, we use such simulations to represent the future behaviour of stock indices, currency exchange rates, interest rates.

An opportunity for learning with the FRM sectors is the use of generative micro-models, such as Agent-based models, to identify and analyse the causal mechanisms that generate the stylized facts used in macro-level models. This could enable system model design practitioners to understand the limitations of certain stylised facts and thus result in the more robust models.

3.10 Conclusion & Further work

The aim of this chapter was to critically review approaches to 'designing for uncertainty' in financial risk management and crowd flow Management and to provide a starting point for the development of a coherent set of 'design for uncertainty' practices.

Our key conclusion was that at present there is little in terms of guidance with respect to designing system models for uncertainty. Neither the crowd flow sector nor the financial risk sector provides a systematic process or a systematic set of techniques for designing for uncertainty. Our survey found that each discipline has examples of system models that address some of the types of uncertainty identified, however, these is little literature on the process of system model design itself. This means that there is a large amount of further work required to move from the artisanal system design approaches that are typical to the disciplines to a more systematic engineering approach where design trade-offs are understood in a quantitative manner.

Further work towards developing a coherent set of 'design for uncertainty' practices would be to develop a systematic and rigorous understanding of popular models/model components with respect to their computational cost and impact on parametric, structural and method uncertainty in various scenarios. This knowledge and the techniques used to create this knowledge could then used to develop a body of knowledge that system model design practitioners can begin to use and refine.

3.11 The cognitive psychology of decision-making, risk taking and assessment

Car or public transport? Desktop or tablet? Save or spend? Life is all about choices, and choices require decisions, both on the way to the office and in economic and financial workplaces. There is increasing interest in the field of decision-making, especially when it comes to risky versus cautious ones that are related to the challenges of market choices. These decisions become more pertinent in a technologically advancing but uncertain world, where unpredictability is high, where polls and wrong, and when information is highly imperfect.

The sciences behind human decision making span everything from evolutionary biology to sociology, and its roots go back centuries (Glimcher 2003; Cohen 1981) to seers predicting the weather to shamans predicting the onset of disease. In the modern age, economists attempt to foresee how consumers will change their behaviour in the face of tax changes, or and politician try to predict how whole economies will react to trade and tariff changes, for example. Behind all if these changes are individual decisions, which scale up from people to communities all the way to whole countries, and further still to federations of them.

There are two fundamental questions at hand: first, how do people make decisions? Second, how (in an ideal world) should decisions be made? (There are of course the allied queries of what are good judgements actually are, and how we can recognize them? The investigation of how people make decisions (behavioural judgement or decision research) has been influenced by two premises: first, that the objective of decision making is to make the 'best' choice; second, that that the best choice can in some way be computed.

3.12 Examples of early behavioural decision research

An early central concept in behavioural decision science is 'subjective expected utility': the attractiveness of an economic opportunity to a decision-maker in the presence of risk. However, 30 years after its introduction and early examination, a literature review by Muermann (2004) described how its critics were now the majority over its supporters. Other researchers agreed that traditional subjective expected utility was a good standard model, but that it was not a good fit for people's behaviour (Laciana, Weber, Bert et al. 2007).

A considerable quantity of empirical evidence has been compiled that indicates that subjective expected utility does not predict human decisions. For example, Edwards (1955) found that when offered a choice, most people have definite preferences between bets of expected equal value: compared to a good chance of winning a small amount, subjects preferred a long shot of winning a larger amount – but only if there was no chance of losing a lot, which people where averse to, even if the probability of losing a lot was low. Edwards' conclusion was that subjective expected utility was not guiding participants' choices. This may have been because subjects did not understand expected value, and Lichtenstein, Slovic and Zink (1969) found this was the case even if the expected value concept was explained.

Later, the 'preference reversal phenomenon' on bets with non-equal outcomes was detailed: choosing a safe bet, which that has a large chance of a small gain, over a longer shot that has small chance of a larger gain. Slovic and Lichtenstein (1968) noted that the attractiveness of a bet's proposition was strongly influenced by the outright probability of winning and losing. However, when faced with paying to take the gamble (or the smallest amount they would sell it for), subjects were then more influenced by the actual win or lose quantities.

This finding has since been replicated many times (e.g. Slovic 1995) and undermines the drivers of rational choice presented by the subjective expected utility. Grether and Plott (1979) found the same results, even when the experiments where performed by economists rather than psychologists, and suggest that "no optimisation principle of any sort lies behind even the simplest of human choices".

3.13 Perceiving the risk, and taking the risk

How do people of different cultures perceive risk? All humans have the same physical brains, but we do not all come from the same cultures. What affect might this have on how people perceive risk, and then react in their decisions?

The same variations in experimental outcomes can be perceived in different ways by different individuals and cultures (Brachinger and Weber, 1997; Weber, 2001a, 2001b).

Experiments were conducted by Weber and Hsee (1998) from decision makers in the USA, Germany, China, and Poland, gauging risk judgments as minimum buying prices for risky financial investments. Significant cross-national differences were found, with the Chinese paying the highest prices and people from the US perceiving the highest risks. But after risk perception differences were taken into account across the four countries, the proportion of individuals perceived-risk averse or perceived-risk seeking was not significantly different. ,

Other researchers have argued that an individual's optimal level (or 'ideal point') of risk or uncertainty is not just about minimising it, but could differ according to culture as described above, according to different situations (Weber and Kirsner 1997), or by personality traits (Lopes 1987).Ideal point models (Coombs 1975) assume the riskiness of an alternative is perceived as the deviation between a person's ideal point of uncertainty and the alternative's level of uncertainty. The perceived risk of high level of uncertainty would be relatively higher for a person with a low ideal point; lower for a person with a relatively high ideal point.

What could account for the differences between individual ideal points for risk and uncertainty? These have been investigated in terms of thrill- or sensation-seeking (Zuckerman 1979; Zuckerman *et al*. 1988) which can vary according to personality, sex and age. Weber *et al*. (2002) report positive correlations between measures of thrill-and-adventure-seeking and recreational risk-taking, as well as between and ethical risk-taking and the disinhibition subscale.

Ideal point models predict that variations in risk-taking can be attributed to be differences in the perception of risk and benefits, rather than a difference in outlook towards a perceived risk. So groups known for high levels of thrill- or sensation-seeking, such as teenage boys or extreme sports enthusiasts, undertake riskier behaviour because they perceive the risk to be inherently smaller or the benefits larger than other groups (Hanoch *et al*. 2006).

3.14 Assessing risk-taking behaviours

How can assessments be made of risk-taking? It's important for the experimental methodology to have a strong affinity to the real-world risk-taking scenario that it is looking to model. . Some models also work better in certain domains over others. For instance, the utility assessment tools such as Holt and Laury (2002) on lottery choices are better predictors of risk-taking behaviour in monetary gambling choices than in making farming production decisions. Likewise, Weber *et al*. (2002) reported that the gambling subscale of their Domain Specific Risk Taking (DOSPERT) scale was a better predictor of self-reported gambling behaviour than the monetary investment decisions that the model was originally developed for!

In assessing risk-taking, it is also important to scrutinise details of the risky behaviours. Are they one-shot risks, like a lottery ticket? Or sequential one-shots that do not alter the odds, like slot machines? Many real-world risks give feedback as a person is involved in a series of linked decisions. Unsurprisingly, assessing risk in these repeated feedback-oriented dynamic requires different models, such as the Balloon Analogue Risk Task (BART) by Lejuez *et al*. (2002) or the Columbia Card Task (CCT) by Figner *et al*. 2007).

Assessment procedures are even more complex when the goal is intervention-based and seeks to alter the risk-taking behaviour in some way. In these instances, researchers need to use assessment techniques that can measure the risk in ways that are not confounded my other variables (similar to epidemiological studies, for example).

3.15 Different theories in decision-making

In studying decision making, psychologists are interested in the dichotomy of what we 'should' do, compared to what we actually do. Consequently, two types of theory of decision making have been described: the standard (should/ought to) and descriptive (what we do) models.

The standard theories attempt to define hypothetical ideal decisions, while descriptive theories attempt to characterize how people actually make decisions. It is worth noting briefly that this suggests there is something profoundly wrong in how people make decisions. But seen through the lens of other fields e.g. memory and vision research, researchers there do not assume that just because people do not have 100% recall of every event in their lives, or cannot see and comment upon everything in their field of vision, that most people's sight and memory isn't perfectly sufficient for a fully functional life.

People make and decisions judgements that are inconsistent with standard theory – we are interested in why this is, how people arrive at these decisions, and what interventions could be made at certain times to change behaviour.

Hence, a third research theme navigates between the standard and descriptive, the prescriptive approach, which explores how to assist better decision-making processes. For example, decision analysis tries to help people make decisions that more closely match those of standard theory. It uses a number of techniques, such as decision trees that deconstruct complex decisions into smaller, more manageable parts.

3.16 Subjective utility theory

From deciding whether to take out private health cover to what grade of travel insurance is needed for a holiday where there might be an element of risk, say a possible white water rafting trip, life is full of decisions about risk when the possible outcomes are unknown or uncertain; after all, the rafting trip might be on grade three, four or five rapids depending on recent weather. And typical investment decisions often centre on whether to make a safer investment or a riskier one, and how much to invest so as to not lose everything – or what is perceived as too much. These kinds of decisions can be analysed as gambles, because there is information available, but also uncertainty.

A much researched standard model of risky choice is called 'subjective expected utility' (SEU) theory that has its origins in 'expected utility' theory published by von Neumann and Morgenstern

(1944) in their Theory of Games and Economic Behavior book, which was then expanded upon by Savage (1954). Savage's extension brought in 'personal probabilities' (now 'subjective probabilities') and allows it to be applied to decision-making situations where judgements are just stated beliefs about likelihoods and no objective statistical probabilities are available. Think mulling over an invitation to a music gig by a friend when you don't know which friends-of-friends will be attending, or anything about the band.

In standard economic theory, a rational decision would be trading off the value of possible outcomes (great bans, can't see; rubbish band, good view etc.) and the likelihood of obtaining them. But what is the value of an awesome gig, and how can you predict of you'll like your friend's friends? What this shows is that people don't have a set of stable, pre-existing values – one day you could be up for new people and new music, another day this is not desirable. People's preferences change, and this affects their decision-making.

3.15 Prospect theory: taking account of changing preferences

Decisions change because of movements in the fundamental landscape in which decisions are made, all of which makes it hard for researchers to qualify and measure. Kahneman and Tversky (1979) proposed a descriptive model for decision marking under risk, ‘prospect theory’. It is a descriptive, not a standard, theory and unlike the SEU, prospect theory does not define an ideal choice. Instead, prospect theory identifies two choice processes: 1) the editing phase, when the decision problem is characterised and a reference point constructed to allow scoring of gains or losses; 2) the evaluation phase, where attitudes towards risk and identified gains and losses are made.

Prospect theory proposes that people compute outcomes in terms of gains or losses that forms a neutral reference point. For instance, the difference in value between £0 and £10 feels much bigger than that between £100 and £110, even though the intrinsic amounts are smaller.

Prospect theory also models the observation of loss aversion, in that people feel losses more than gains of the same value. Prospect theory’s weighting function can also account for behaviours observed in the Allais paradox – the inconsistency of actual observed choices with the predictions of expected utility theory. People weight probability below certainty much less than they should, giving certainty a relatively very high value: 100% certainty is weighted a good deal more than 99%, and hence people worry disproportionately about the 1% chance of not winning.

Prospect theory is described as account of decision making under risk situations, but there are many examples of this model being used in riskless choice circumstances in the literature. For instance, in loss aversion robust laboratory studies using ordinary consumer goods have shown that the minimum amount of money a person will accept to part with an object generally exceeds the minimum they will pay to accept (Horowitz and McConnell, 2002). Moreover, in a phenomenon known as the endowment effect (Thaler, 1980): people often value objects more highly when they come to feel that they own them. In a Kahneman *et al*. (1990) study, this was evidenced by sellers quoting $7.12 for a university mug they ‘owned’, whereas the buyers offered less than half the price ($3.12). To the sellers, it was a choice as a loss of a mug against a compensating gain of money; the buyers presumably framed the choice as a gain of a mug against a gain of money.

3.16 The influence of loss aversion

This loss aversion contributes to people's tendency to stick with the status quo (Samuelson and Zeckhauser, 1988) and be reluctant to engage in new or innovative trades. Knetsch (1989) demonstrated this in a study where students were offered bar of chocolate or a university mug and showed no significant preference. But when they were assigned the chocolate or mug randomly, nearly 9 out 10 retained their original choice whether they got the mug or chocolate first, showing that people won't trade unless stimulated to do so.

Loss aversion has thus been used to explain anomalies in field data, and how people retain default positions. For example, organ donation rates in European countries are much higher with an 'opt-out' policy (so the default position is 'in') than in countries where you have to 'opt-in' (Johnson and Goldstein, 2003). Consumer demand is also more sensitive to price increases than decreases (Hardie *et al*., 1993) showing shoppers' stronger aversion to the potential loss of price hikes.

Stronger responses to losses than gains are also seen in evaluations of fairness. People don't like the idea of shops increasing the prices of umbrellas in rainy weather. Specifically, most people see it as unfair if employers raise prices for consumers – unless they are reacting to their won losses, such as higher trade prices or tax hikes (Kahneman *et al*., 1986). Similarly, people consider it fairer to remove a rebate than bring in price increase on customers, which politicians use to their advantage in balancing tax demands for example.

To find out of there was any consistency in a person's loss aversion across risk vs riskless settings, Johnson *et al*. (2007) determined car customer's coefficient of loss aversion in a risky context, as well as a riskless one. Their results had a statistical Spearman correlation between risky and riskless measures of .635, suggesting that loss aversion is a consistent, fundamental trait that affects a wide variety of decision-making.

3.17 Risk-taking and domain differences

Early attempts to bring consistency to decision-making research methodologies highlighted two components to consider when constructing experiments to determine how people measure risks: 1) taking account of the often decreasing marginal value of outcomes (e.g., two free mugs are not twice as rewarding as one free mug); 2) measuring typically averse attitudes towards risk, which can result in a ‘risk premium’.

Potential domain differences in the marginal values of riskless choices can be factored out of a risk attitude assessment, as shown by Dyer and Sarin (1982) who replaced the Arrow-Pratt (1964) measure of absolute risk-aversion (ARA) with what they referred to as relative risk attitude (RRA). Later, when Keller (1985) compared people’s Arrow-Pratt measure of risk attitude (ARA) to their RRA, she found the two figures only agreed in for a small number of cases, and that for any one person, RRAs do not show more consistency than the original Arrow-Pratt ARA measure.

This issue of inconsistency in risk-taking in different decision areas is not directly addressed by prospect theory, but because it is a descriptive theory of choice, it suggests reasons why risk-taking can seem unstable. Firstly, the framing of a problem can change decision-influencing reference points, which then changes the apparent risk attitude. Secondly, an individual’s extent of loss aversion differs for different outcomes in different domains.

So could prospect theory account for domain differences in risk-taking? Gaechter *et al.* (2007) provide evidence addressing the question, suggesting that loss aversion can differ for different attributes. In this instance, they make it as a function of the importance of the attribute, and the expertise (if any) of the decision maker in that domain. Extensions of such risk-return models (e.g. Sarin and Weber, 1993) account for these domain differences by questioning the return with expected value, and looking at risk with outcome variance. For example, in populations that differ in risk-taking behaviour, survey data suggests that risk-takers judge the expected benefits of riskier choice options as higher than in control groups of those less inclined to risk (Hanoch *et al*., 2006).

3.18 Perceptions of risk

A significant body of literature has investigated the perception of risk, using direct methods such as data collation and modelling, and by using metrics that serve as proxies of risk-taking behaviour (Weber, 2001a). Papers in this field commonly state that the standard deviation or variance of outcomes does not account for perceived risk, for the following reasons. For instance, Luce and Weber (1986) describe how deviations contribute symmetrically to the statistically defined variance above and below the mean, but the perception of riskiness is affected to a greater extent by downside variation.

Moreover, affective responses (i.e., non-rational or nonconsequential) to risky situations can play a significant role in both the perception of risky choice options and in the risky choice itself. Finally, behaviours involving risk perception are influenced more by experiences in the more rennet past and are affected by the emotional reactions connected to these recent outcomes.

3.19 How to measure risk attitude

The literature reviewed indicates there is no 'one-size-fits-all' measure or index of a person's (or organisation's) risk attitude. It is made up of a series of interconnected factors that influence it in different ways and to vary extents. However, one way to approach this difficult task is to look at whether the risk assessment is to be used for intervention or prediction.

For predictive purposes, a decision task as close to the situation as possible should be used, such as using risk assessment questions from the same domain and matched to similar targets. In this vane, Weber *et al*. (2002) found that assessed risk-taking for investment decisions performed better than in monetary gambling decisions.

So it follows that risk-taking indices of relative risk aversion measure inferred from gambling choices (by Holt and Laury, 2001, for example), have had mixed results in predicting risk-taking in other areas, despite being widely used.

Alternatively, for intervention-based goals it is crucial to understand the root processes of the risk aversion (or risk-seeking), as seen in different attitudes to risk between men and. A better resolved assessment of the fundamental determinants of risk-taking is important here, because the different drivers of behaviour should play a significant role in designing the appropriate intervention

3.20 'Hands-on' heuristic learning and the 'dual-process' brain model

A classic issue for researchers is the disparity between results that are gathered in controlled laboratory experiments versus studies 'in the field' where parameters cannot be so carefully controlled, but offer more realistic test conditions. Studies in the field of decision-making are no different, and researchers such as Gigerenzer and Goldstein (1996) have pioneered new methods on the efficiency of heuristics (using practical rules of thumb') away from lab- or office-based simulated models to test sets of various decision strategies. They developed an efficacy-based measure of basic mental judgement strategies by measuring correct inferences from different decision-making strategies.

Gigerenzer and Goldstein coined the terms 'fast' and 'frugal' heuristics: 'frugal' because they only one piece of information, and 'fast' because they didn't attempt to integrate additional information from other normative techniques like SEU or Bayer's Theorem. The mental strategies the two researchers tested look simplistic and violated certain principles (e.g. transivity), but there is a case for such violations – people do this when they make decisions, which is the very process researchers are attempting to model. Indeed, other researcher such as Simon (1956) have highlighted that because of the human brain's limitations, it is to be expected that the processing of information will use short cuts for time-efficient problem solving.

In their experiments, Gigerenzer and Goldstein asked participants to judge which was the biggest German city, based on properties or correlating factors such as whether it has a university, a top division football team or a major intercity train station. One heuristic they tested was called ‘take the best’, because it took each cue in turn according to predictive validity until it correctly differentiated between two cities e.g. one has an intercity rail station. Note that this is similar to how people ordinarily come to snap judgements: “It has a cathedral it is a city” or “this area has lots of bars this is the cool part of town”.

Gigerenzer and Goldstein then compared ‘take the best’ and other simple heuristic decision rules that integrated more information. Against expectation, they found that ‘take the best’ performed well, or even better, against other algorithms with more data. These results

demonstrate that adhering to normative rules is not always necessary for good judgement, and using one dimensional heuristics can be quick as well as effective.

Binary decisions have further tested fast and frugal heuristics across a wide range of knowledge environments, applying the choices to categorisation, memory skills, and value estimates (Gigerenzer et al., 1999). For example, Goldstein and Gigerenzer (2002) asked German and American students which city is larger: San Antonio or San Diego? 100% of German students were correct, compared to 62% of American students. In this case, the Germans applied recognition heuristic: if in doubt, pick the one you’ve heard of! This works because we hear about the bigger cities in other countries more often that the smaller ones. The Americans will have heard of both, so weren’t able to apply this cue so well. This illustrates that, paradoxically for a knowledge test, a certain level of ignorance can be useful for making effective inferences. These studies rightly bring us question the high status of normative rules that set standards in the assessment of human judgement.

Significance of the ‘dual-process’ model of the brain

The dual-process theory of the brain is a key factor in understanding the neurobiology of the processes under which financial decisions are made. This popular theory is now applied widely in psychological studies of decision-making and learning. It describes two different modes of neural processing: ‘system 1’ operates automatically, quickly, and intuitively without conscious control, and with little to no effort. By contrast, ‘system 2’ is characterized by, analytical, deliberate and logical thought and so is slower than system 1. Daniel Kahneman (2011), a psychologist well-regarded in this area, describes system 1 as the real 'hero.' in that we are born its attributes to perceive and orient to the world around us, recognise items and avoid material losses. Over time and through experience, many neurological activities of system 2 become more automatic and thus handled by system 1 – including the associations between concepts or ideas. System 1 also takes on learned skills, such as reading or driving, which at first take considerable effort but later can be done alongside (to varying degrees) alongside other tasks.

3.21 Decision-making, memory, and the dual-process model

It is important to consider memory when examining decision-making and dual-process theory. It is theorised that system 2 requires access to working memory, but system 1 does not. This is an important distinction because working memory has a limited capacity, and system 2 depends on it, which results in its slower processing, lower capacity and higher effort demands.

The two systems can be seen as a way to optimize performance and minimise effort, and both are active whenever we are awake. They are not completely independent of each other, but work together, providing the basis of processing and decision-making, with system 1 running automatically while system 2 awaits system 1 to engage it with more demanding tasks, calling on it to sustain more complex and precise processing to address a problem. When system 2 integrates system 1’s submissions with next to no modification (or none at all), it is referred to as intuitive judgment. Hence, system 1 makes intuitive impressions are based around heuristics, which all people subconsciously use for decision-making, whether they are aware of it or not.

However, because system 2 can adapt system 1’s intuitive suggestions without modification, this can lead to apparent errors in judgments. Since we believe the two systems work together, any error of judgment thus involves the failure of both systems: the origin of the error lies with system 1, but system 2 did not detect and correct it.

System 1 dominance and decision-making

In terms of financial decision-making (and in many other realms) the question of why system 1 appears to dominate system 2 (or why system 2 does not more easily override system 1) is of considerable theoretical practical interest. Some theories suggest that this domination is because people are unmotivated to fully process the relevant information, describing system 2 as a ‘lazy’ system that is too accepting and trusting (and too uncritical) of the suggestions it takes on from system 1.

Another theory posits that people are often unable to fully process all of the appropriate information, and that the effort and amount of information needed is greater than working memory's capacity, and this information overload leads to a 'system crash' of sorts.

According to [75], a successful system 2 intervention over system 1 may be cued by better deductive reasoning skills, and is more likely if individuals are able to think more critically or reflectively, and have a higher working memory capacity.

Integrating the dual-process theory into financial decision-making

Looking at decision-making through this dual-process theory, financial analysts engage in a lot of mental effort and attention using system 2, especially when they are novices and utilising new data and unfamiliar operations. But over time as they gain experience and are more familiar with all aspects of the role it becomes more automated by system 1. This is called implicit learning in dual-process theory, because so many of the requisite skills are learned without conscious awareness. The activities of musicians and athletes are also good examples of implicit learning, because at first the demands of learning and following the rules, as well as the mental and physical agility required, require significant system 2 rational thinking until experience takes over and conscious attention is then no longer necessary to orchestrate the complex, coordinated movements (Kruglanski et al., 2011; Beilock et al., 2004).

System 2 may intervene more if individuals can think more reflectively or critically. Add to that experience in a certain sphere that could increase the ability to think more critically, means that system 2 interventions could be expected to occur more frequently in individuals with greater experience. This suggests that individuals with more experience could use logic more in their reasoning and be better at suppressing the impulses that bias their decisions. Research from [72] and [73] supports this theory, and they suggest that effective systematic processing requires working memory capacity and cognitive ability.

What we would expect to see from a synthesis of these ideas is that more experienced decision-makers exert less effort as well as making better, more accurate decisions. Although it might not always be seen on financial trading floors, it can be seen in activities like driving a car or diving, where more experienced drivers and divers are typically safer and better than inexperienced one, despite that fact that less conscious effort is made in their actions. For financial decision-making, dual-process theory predicts that more

experienced traders and investors should use less effort to make more objective and less belief-based) decisions.

3.22 Risk: assessment, perception, aversion and tolerance

With risks come gains, but there are also losses. A common phrase on TV and print adverts for financial services products reads: “The value of your investments can go down as well as up”. People assess, perceive and handle risk in different ways, and this affects their present and subsequent decision-making abilities. People with greater wealth could be expected to take greater risks because any loss will have a smaller impact on their overall wealth, which can be measured in terms of hard currency reserves, property ownership, pension values (Brayman, 2013), future earning ability, and other factors that affect daily budgets such as insurance costs (Samuelson, 1969), and finally loans and credit cards debts. The intriguing question is: what affects how much of that wealth is a person or group willing to risk?

The first two basic factors are actual amounts and proportions of wealth. A 20% loss with a £5 million portfolio will still leave a considerable sum of £4 million to that investor. It’s a (relatively) massive loss, but £4 million is more than enough to meet daily costs well into the future. But the consequences of and investor losing £20,000 out of £100,000 – still the same proportion of 20% -- are much more significant. Note that this is not consistent with the ‘relative risk aversion’ concept that states two individuals with the same utility function are expected to feel the same disutility from a 20% loss in total wealth. Clearly, the investor losing 20% of £100,000 is much worse off, even though the proportional loss is the same. The percentage of wealth subject to risk is a key factor.

3.23 Assessing risk

Assessment of risk capacity can be seen as an objective evaluation of financial risk tolerance i.e. how much you can afford to lose. Hanna, Waller and Finke's (2008) model proposes that a person's risk profile is the sum of a) objective factors that a financial advisor can clearly see, and b) subjective factors that are best recorded through a proper risk-tolerance assessment tool. Other relevant factors include income and outgoings volatility (and the fact that people might withhold sometimes crucial information from their advisors e.g. pending divorces, debts). Time horizons (a fixed point of time in the future when certain processes will be evaluated or assumed to end) can also be included, although some such as Bodie (1995) argue that time horizons are (theoretically) not related to optimal portfolio allocation unless considered with a client's 'human capital', such as their age and retirement plans, for example.

Following on from objective measures, subjective risk preferences can be thought of as the factors that influence the impact of various investments on the client's general well-being or happiness. An identical investment can have different subjective effects on a couple that have just lost half of their life savings, compared to a couple across the street who recently doubled theirs, through a fortunate inheritance for example. A Palma and Picard (2010) review concludes that economic concepts of risk tolerance are clear enough, but measuring it is more opaque. A proper scientific evaluation of especially subjective risk factors is still in its infancy, even by financial advisors who often resort to heuristic measures in questionnaires.

Hence, a key factor in a client's inclination to take on risk is experience and knowledge of financial decision making. In this aspect, a client's level of education, independent of income and wealth, is not necessarily a good predictor of risk tolerance – many very well educated people go bankrupt. In terms of 'risk perception', people that are more financially literate are reliably more disposed to accept financial risk. They may be better able to understand the basic principles of accepting risk to achieve long-term financial goals, as well as being prepared for future financial performance variations.

When accepting investment risk, Dow, Da Costa and Werlang (1992) note that clients should be made aware of the likelihood or distribution of potential outcomes. People with a lower level of education or financial literacy (or less investment experience) will be less certain about the risks, and tend to exhibit 'ambiguity aversion', where a preference is shown for known risks over unknown risks where the consequences are more ambiguous.

3.24 Measuring risk tolerance

Risk tolerance is defined economically as a variation in future spending. So, economists utilise questions related to measuring income volatility to assess risk tolerance e.g. "would you choose between more job security and a small pay increase, or less job security with a big pay increase?" Although theoretically sound, in surveys the performance of these questions as predictors of real investment behaviour is mediocre, as found by Guillemette, Finke and Gilliam (2012), especially in volatile stock markets.

In the analysis of portfolio allocation between a high-risk, medium-risk and low-risk assets, Guillemette, Finke and Gilliam found that these income risk questions regarding investment portfolio choices are consistent with conventional utility theory (the preferences of a set of goods or services that is satisfying to the chooser). The same income risk questions were also good predictors of whether people cashed in their portfolio during the 2008 financial crisis. Other queries, such as a self-assessment of respondents' willingness to take risks, as well as questions that gauged

behavioural responses to risk were even better predictors of both response to an investment loss and portfolio preference Linciano and Soccorso (2012).

Other questions to measure financial risk do not correlate so well. In a large national data set, Grable and Lytton (2001) found that a financial risk assessment instrument did not correlate well with a series of questions relating to gambles that involved the possibility of a loss. This suggests again that there is an emotional response to potential losses, not just rational decision-making, when portfolio investment choices are presented.

A number of ideas presented in Kahneman and Tversky's (1979) 'prospect theory' are important to risk tolerance assessment activities. For example, when assessing risk, people tend to begin their assessments of potential wins and losses from an arbitrary starting point – the 'reference point' – which can be an amount invested, or asset values from or in a given time e.g. calendar year, or quarterly results. Another key aspect of prospect theory is 'loss aversion', in that people in general respond about twice as much emotionally to a loss than to an equivalent gain. Furthermore, this emotional response is related to whether the value of the loss falls beneath the earlier reference point.

3.26 Limitations of traditional models in finance

Traditional finance models have allowed little room for the role of emotion in decision-making. Indeed, they represent individuals as interested agents who attempt to optimise to the best of their ability in the face of constraints on resources. Markets are viewed as efficient, meaning that price coincides with the fundamental value and is influenced by supply and demand as exemplified by the efficient market hypothesis (Fishburn, 1988).

These traditional finance theories make three fundamental assumptions about individuals. Firstly, individuals have rational preferences across possible outcomes. Secondly, they strive to maximise utility in that they wish to maximise the total value derived from the available money. Finally, they make independent decisions based on all relevant information. Traditional finance models thus hold the 'Homo-economicus' (Drucker, 1939) view of individuals as rational, unbiased and unemotional individuals. Decision-makers are to consider all relevant information and come up with the best decision under the circumstances.

However, in reality we have limited processing ability and therefore use heuristics (rules of thumb, practical ways to get things done), are prone to inattention and biases (Deaves, Dine, & Horton, 2006). Moreover, contrary to traditional finance models' predictions of an efficient market based on rational decisions, Daniel et al. (2002) found that investors systematically deviate from optimal trading patterns.

3.27 Behavioural finance and newer models

The field of behavioural finance challenges the assumptions of traditional finance theories by incorporating these observable, systematic departures from rationality into finance models. The goal of behavioural finance is to understand psychological biases that affect investment decision (Peterson, 2007) because reducing these errors would lessen their effect on financial decisions, leading to potential improvement such as greater investment results (Kuhnen & Knutson, 2005).

Behavioural finance researchers posit that because human information processing capacity is finite there is a need for abbreviation of decision processes or heuristics to arrive at decisions in the most cognitively efficient way (Tversky & Kahneman, 1974). This heuristic simplification process, according to Hirshleifer (2001), can explain most psychological biases including emotion-based judgements. Such emotional biases potentially lead to irrational decision-making (Kahneman & Riepe, 1998). As such, inherent to behavioural economic theories, is the view that emotions hinder financial decision-making and should be countered and controlled so as to attain the most efficient trading performance.

According to Kahneman and Tversky's (1979) behavioural model of prospect theory, individuals make decisions based on the potential value of losses and gains rather than final outcome. Decision-makers set a reference point for each decision and from this point evaluate potential outcomes. Lesser outcomes than the reference point are considered as losses and greater ones as gains. The resulting S-shaped value function is asymmetrical: loss hurts more than gain feels good, and these are also dependent on whether they were followed by a loss or a gain (Tversky & Kahneman, 1991). As such, individuals are not uniformly risk averse as suggested by traditional models (Bowman, 1984) but adopt a mixture of risk seeking and risk averse behaviours. When returns are below the reference point most individuals are risk seeking, and when returns are above the reference point most are risk averse (Fiegenbaum and Thomas, 1988).

Assessment of individual risk attitude has been central in financial decision-making theory and practice (Cho & Lee, 2006). Fellner and Maciejovsky (2007) found that individual risk attitude was systematically related to market behaviour. High-risk aversion is associated with lower observed market activity and more cautious behaviour thus translating in lower returns and volatility (Barber & Odean, 1999). As such, although behavioural finance has now acknowledged and integrated the effect of psychological and emotional factors, such as risk aversion, it would appear that they still perceive emotions as hindering decision-making, approaching emotions as bias inducers.

3.28 The introduction and influence of neuroscience

Research into the neuropsychological underpinning of emotions has lead psychologists to take a radically different view, perceiving emotions as facilitators. Indeed, neuroscientific research has introduced a process theory of decision-making based on anticipation of various emotional reactions to outcomes (Bossaerts, 2009). Emotions are posited to be an integral part of reasoned decision-making and are believed to actually improve the process (Bault, Coricelli, & Rustichini, 2008).

In fact, Bechara and Damasio (2005) suggest that emotional processes guide reasoned decision-making. For complex choices or when the stakes are high, cognitive processes are unable to lead to a decision. Damasio's somatic marker hypothesis describes somatic markers as the association between relevant stimuli and induced physiological affective states (Bechara, Damasio, and Damasio, 2000) which recur and lead these cognitive processes. The somatic marker association is thought to be processed in the ventromedial prefrontal cortex (vmPFC) (Damasio, 1989). This neurological region was found to be the interface between visceral reaction and higher cognitive functions and thus postulated to hold the association between the facts that compose a given situation and the emotions previously paired with it (Damasio & Damasio, 1994).

Empirical support for the SMH has been based on the Iowa Gambling Task (IGT) an experimental paradigm designed to measure decision-making (Bechara, Tranel, Damasio, & Damasio, 1996). During the IGT researchers assessed individual participant's levels of autonomic arousal through the galvanic skin response (GSR) measurements. GSR is a method of measuring electrical conductance of the skin which varies depending on the state of the epidermal sweat glands (Boucsein, 2012). As sweating is controlled by the sympathetic nervous system, GSR is used as an indicator of psychological and physiological arousal (Martini & Bartholomew, 2001).

Research has consistently found that successful performance on the IGT is correlated with the development of somatic marker signals as indexed by anticipatory GSR in healthy control participants. Crucially, patients with vmPFC lesions would consistently opt for the wrong decision and fail to express emotional anticipation when making a risky decision (Bechara, Tranel, & Damasio, 2000), thus indicating the fundamental and beneficial role of anticipatory GSR in decision-making. Furthermore, in a review of the literature on decision-making measuring GSR, Dawson et al. (2011) concluded that when making a significant decision or when presented with a stimulus with a possible negative consequence in anticipation of that outcome, GSR are likely to occur.

Thus, a fundamentally different account of the role of emotion is given by neuropsychological research and theories. According to the SMH, emotions in the form of anticipatory GSR are important and functional cues, signalling possible negative outcomes without which dysfunctional decisions are made.

3.29 Emotions and financial decision-making

Although recent neuroscientific studies have examined in great depth the process by which emotions influence decision-making under conditions of risk and uncertainty, few studies have examined the specificity of financial decision-making. It is important to examine emotions in financial decision-making specifically to assess whether emotions are particularly hindering to decision-making, as posited by financial theories, or whether emotions in financial decisions are facilitators as hypothesised by the SMH.

Lo and Repin (2002) are among the few to have examined trading patterns and daily affective reactions. They measured GSR of financial securities traders during their trading activities. They found that during salient market events, GSR measurements were elevated, suggesting that emotional responses are a significant factor in real-time financial processing. GSR responses were found to be significantly different during transient market events relative to no-event control periods, both before the event (anticipatory) and after the event (post). Interestingly, contrary to the SMH predictions they did not find any difference between anticipatory and post GSR.

SMH theory emphasises the cueing role of emotions in decision-making, so anticipatory GSR would be expected to have been heightened in comparison to post GSR as somatic markers signal a potential negative outcome. Lo and Repin (2002) concluded that this lack of difference implied that their measures were unsuccessful in assessing anticipatory emotional responses and potentially significant methodological issues were highlighted. Namely, their inability to relate psychophysiological responses directly to a trader's financial gains and losses. Furthermore, their window for anticipatory and post GSR was 10 seconds – meaning that the two responses could possibly overlap, thus offering another possible explanation for the lack of difference between anticipatory and post GSR. Moreover, the sample size was very small (10 professional traders). While this study has brought forth important findings, for these to be fully taken into account, they need to be replicated in a methodologically sound manner.

In another study, using a different paradigm and a bigger sample of 80 future trader volunteers, Lo et al. (2005) investigated further the link they had previously established between emotional reactivity and trading performance. Using daily emotional state surveys over a five-week period they constructed measures of affective states for each participant and correlated them to profit and losses. Reporting extreme emotional responses whether negative or positive was found to be counterproductive from the perspective of financial trading performance. The authors thus propose that the affective state of the decision-maker may characterise dysfunctional financial decision-making. A two-dimensional approach to affect examining both valence (intrinsic attractiveness or averseness) and arousal (the strength of emotional response) has been frequently suggested in the literature (Mano, 1992; Heller, 1990; Lang, Bradley, & Cuthbert, 1990). Such representation would lead to a greater understanding of the interaction between affective states and decision-making (Mano, 1994).

3.30 Integrating different approaches

As we have seen, economists focus on the detrimental effect of emotions in financial decision-making, while psychologist emphasises the crucial and beneficial role of emotions in this process. According to Camerer et al. (2004) a biological basis for behaviour in neuroscience combined with financial theories, such as prospect theory, may provide some unification across these approaches. These authors believe that neuroscience should inform economic analysis (Camerer, Loewenstein, and Prelec, 2005). They conclude that side-stepping biological and cognitive sciences that focus on the brain, which is the building block of the economic system, may prove to be dangerous to the field (Camerer, Loewenstein, & Prelec, 2004). Indeed, recent neuroscientific research such as work by Lo and colleagues has been remarkable in offering an insight into the actual mechanism by which emotions influence financial decision-making. However, as we have seen these studies are limited and crucially do not integrate past financial theories.

Our study will thus further the field of financial decision-making by examining the role of emotions, using contrasting economic and psychological approaches. Crucially, we will build upon Lo and colleagues findings, countering their limitations and assuring their validity. Furthermore, by combining psychologically driven measures of self-reported emotional states, physiological measurements of arousal and economic models of behaviour, this study will be able to assess and combine neuropsychological approaches to emotions with more financially driven models. Finally, our study will go to the heart of the subject by examining trading performance during boom and bust market situations.

3.31 herding behaviours, Emotional factors

What are herding behaviours, and under what conditions are they likely to occur?

Herding phenomena occur when an individual's private information – or that or many individuals – is overcome by the more powerful sway of publically available information about the decisions of a group (that is 'the herd').

Herding behaviour occurs because, in a world of uncertainty or imperfect information, if we appreciate that our personal judgements are also imperfect then it can be considered rational logic to assume that others maybe better informed, and thus to follow their lead (Keynes 1930). Many herding models assume that social information about other people's decisions is used in a Bayesian reasoning process (that the probability of an event occurring can be based on prior knowledge of conditions related to the event) in which people adjust their prior expectations as new public information is received, such as share prices or profit expectations. If subsequent decision-making is based upon logical Bayesian-style judgements that are updated systematically, then the rational updating of probabilities via new information is expected to spread information related to other's choices through a wider community (the herd), leading to herding behaviours and information cascades.

3.32 Are we always rational?

While these are the simplest theoretical ways in which information can be shared, the world and the people within it are not always guided by rational behaviour. Outright intelligence, propensity to take risks, as well as access to information limit the application of Bayesian-type algorithms to determine decision-making. Bayesian-style social learning can still emerge, and is likely to because people like to use rational ‘rules of thumb' and their own personal practical quick fixes to whatever works (heuristics). Therefore, herding can occur because people tend to use easy decision-making tools, including that others are likely to know more about e.g. the long-term values of certain assets.

Social and psychological factors like peer pressure can also encourage individuals to follow other people’s decisions — even when presented with clearly contradictory data. The picture is complicated by a person’s age, gender and personality traits that can affect how easily they are swayed by social-psychological influences. Regarding personality traits, it has been reported that their importance is consistent with other analyses that focus on the role of emotions in financial and economic decision-making (Elster 1996; Kamstra et al. 2003; Lo et al. 2005; Baddeley 2010).

3.33 Theoretical bases of herding influences

Why does herding occur? Why is it so hard for people to follow the ‘correct’ course of action? There are many explanations, which draw on sociology and psychology, as well as economics and mathematical theories. Explanations can be considered under the brad brush of ‘bounded rationality’: that is: in an uncertain world, people’s rationality is limited by the difficulty/solvability of the problem, their own cognitive limitations, and the time available.

In short, it could be said that (and especially when we are rushed) there is not always a perfect response to some decision points. But what could we expect to happen when decisions cannot be delayed, and have to be made – as is so often the case in fast paced offices, from publishing to banking and politics. Under these circumstances, people adopt herding as a result of our heuristic tendencies – a decision-making short-cut, something that (we believe) just works. In this case, personality traits and other social and psychological factors are key determinants of a person’s likelihood to resort to rules of thumb and heuristics.

3.34 Other factors affecting herding

Several microeconomic models of herding describe it as a rational learning process, but where decisions across the herd reinforce each other and are thus interdependent.

We have detailed how herding can be described as a bounded rational response to imperfect information, which then generates convergence towards an outcome determined more by social information and herd actions over private information. Bikhanchandi, Hirshleifer and Welch (1992, 1998) have developed a model which works on this basis, where in sequential decision-making (when each decision conveys no real new information to following members of the herd) informational cascades emerge when it is optimal for an individual to follow the actions of their predecessor instead of their private information. Just as is seen in Banerjee‘s model In both models,

When private information is frequently disregarded in herding behaviours, occasionally this can lead to stable outcomes, such as no-one buying a new stock. But convergence towards peculiar and unstable outcomes is arguably a more likely occurrence (Chamley 2003)

3.35 Experiments to test theories of herding

Economic experiments have tested Bayesian theories of rational herding, such as Anderson and Holt (1996, 1997), that confirm Bayesian hypotheses. Some of these experiments have further distinguished herding in general as mimicking behaviours, as opposed to informational cascades that originate from in uncertain scenarios (Sgroi 2003, Çelen and Kariv 2004, Alevy et al. 2007).

For example, Avery and Zemsky (1998) and then Park and Sgroi (2009) allow rational herding and behaviour contrary to herd choices (known as rational contrarianism) in a herding experiment with conditions including multiple states and multiple signals. They find that around 70% of subjects‘ behaviour is consistent with their benchmark for rationality, and conclude that policymakers should not consider all herding as irrational. Moreover, better information and more accurate signals can lead to decreased herding.

Others have adapted Bayesian models to include flexible prices where information cascades cannot occur, such as Cipriani and Guarino (2005). Their models find that a proportion of subjects do not utilise their private information, instead either not trading or making decisions against the prevailing information (contrarian trading).

3.36 The role of individuals in different herding models

Herds result in herd-like behaviour, but it cannot be ignored that herds are made up of individual people. Individuals are different in the ways that they rationalise and apply statistical data, as reported by Salop 1987; Baddeley et al. 2005). These differences in cognitive competence with regard to the use of statistics, for example, may result in 'reverse cascades', which are when 'incorrect' decisions send information cascades the 'wrong' way, away from prevailing expectations (Sgroi 2003). These considerations predict that if herding results from individuals saving time (and cognitive effort, it could be argued) and resorting to practical heuristic decisions, then specific personality types will be more likely to use these practical measures to shortcut difficult decisions. It is in essence the overriding application of common sense in certain situations, known as 'procedural rationality' (Baddeley 2006).

3.37 Emotions and decision-making

Personality traits and socio-psychological factors certainly affect people's decision-making abilities because many decisions are affected by people's emotions, or emotional predispositions (Elster 1996,; Baddeley 2010). Even the weather can impact upon financial decisions, as described by Kamstra et al. (2003) and Hirshleifer and Shumway (2003) – indeed, with certain markets the phrase "the outlook can be described as gloomy" is used, which is almost identical phraseology as used in weather reports.

Using lesion patient studies, Shiv, Loewenstein, Bechara, Damasio and Damasio (2005) identify a relationship between emotional responses and enhanced risk-taking behaviour. Advanced brain-imaging techniques in the form of functional magnetic resonance imaging (fMRI) have also been used by Kuhnen and Knutson (2005) to identify divergences from expected, rational behaviours. This clearly demonstrates that emotions and moods can have significant impacts on financial and economic decisions, so it is likely that there may be certain psychological characteristics in people that also give them a predilection for herd-like behaviours. This should be little surprise to the biologically-minded: humans are animals, and herd-like behaviours have significant adaptive value. Think of shoals of fish, flocks of birds and herds (literally) of sheep that defend themselves from predators by mimicking each other's behaviour. They even do this in the absence of predators – there are no wolves or bears in the UK, for example – which indicates that higher animals get social benefits such as cohesion and feeling 'a part of the crowd' from following predominating signals – even if the information is at sometimes erroneous.

Besides evolutionary principles, theories of social psychology such as that of crowd influence and group pressure — le Bon's (1896) analysis of mob psychology for example – can shed light on the influential factors ranging from the pressure to conform (normative influence), the fear of standing out, and the desire or need to learn from other apparently more successful people. The difficulty is how to add complex social influences into successful Bayesian and non-Bayesian models – just how do you quantify conformity, or the make a fair qualitative measure of the influence that leads to it?

It's established that people follow people, but people will also follow computer-generated decisions. Intriguingly, this suggests that following the herd is not just a facet or aspect of peer pressure or other social influences (Bikhchandani et al. 1992).

Herding behaviour is, therefore, the summary of a complex interplay between the rational and the cognitive, the emotional and instinctive all played out against a backdrop of psychological, sociological and economic and even technological factors. In the last chapter of this thesis, we introduce a model of herding and emotional cascade.

Chapter 4 Commercialising an Investor's Market Risk Profiling

An investigation of the commercialization potential of Investor market risk profiling

4.1 Summary

Regulators worldwide have taken steps to introduce policies, rules, and regulations that require financial planners and other advisors to comply with minimum acceptable standards of practice when providing investment advice to no institutional clients, and one of this advisor role is to evaluate a client's risk profile and/or risk tolerance, which is broadly defined as a person's emotional and financial capacity to take on risk. In this chapter, we look at the process of developing and commercialize market risk profiler.

In a number of consulting sectors, potential products emerge as a result of consultancy activities. These potential products are often unplanned and so there is a need for a method of rapidly evaluating their commercialisation potential. This section identifies a rapid evaluation method, the 'Stage-Gate 3 Scorecard for Project Selection', and applies it to a risk-profiling system developed within a financial risk consultancy.

It is concluded that the Stage-Gate 3 Scorecard is a promising approach for rapidly evaluating the commercial potential of emergent potential products.

This chapter is structured such that in Section 4.2 introduce the reader to i) the purpose and the need of devising such a product ii) literature relevant to rapidly evaluating the commercialisation potential of such products; iii) risk profiling marketplace and associated technologies, Costs and revenues are identified, along with the expected lifetime of the project.

Section 4.3 & 4.4 introduce the case study product and the 'Stage-Gate 3 Scorecard for Project Selection' that will be used to evaluate the commercial potential of the product, and applies the scorecard and identifies the product's strengths and weaknesses.

In section 4.5 we describe the Check Risk Platform development and layout including assumptions, data sources, descriptions

4.2 Introduction

There exists a significant body of knowledge on commercialization and new product development (NPD), which is the process of taking an initial idea to the point of market launch (Cooper 1983). For more than 20years, research has investigated a broad range of concepts related to NPD. These include organisational issues such as organisational structure, management, communication, and management; up-front and detailed development; launch, competition, diffusion, adoption; and finally performance drivers and measures (Guo 2008, Page and Schirr 2004).

The most significant research with respect to evaluating the commercial potential of products is about understanding the drivers of NPD performance and the processes by which new products are developed. Studies of the drivers of NPD performance have been subject to meta-analysis, thereby consolidating the findings of more than 60 studies into statistically significant success factors (Henard 2001). These factors are:

1. product characteristics especially *product advantage* and *match to customer needs*;
2. strategy including *marketing synergy* and *technological synergy*;
3. marketplace characteristics including *market potential* and *competitive response intensity*.

These findings have been recognised as important by the NPD community and so processes have been created to provide 'best practice' guidelines to ensure that organisations are doing the *right projects* as well as doing the *projects right* (Cooper 1999, Cooper 2008).

The Stage-Gate (Cooper 2008, Cooper 2002) is a well-cited NPD process that provides 'best practice' guidelines and will provide the foundation for this work. Of most interest to us is the 'Gate 3 Scorecard for Project Selection' (Cooper 2006). It identifies six factors and 25 key questions to score the attractiveness of an NPD. This scorecard will be discussed and applied in the following sections.

Market risk-profiling marketplace

Under Financial Conduct Authority (FSA) rules, a financial advisor who provides advice regarding investment and retirement plans, including individual retirement arrangements, must follow fiduciary standards rather than suitability guidelines. This rule change has had significant ramifications for those who provide advice about retirement plans in the United Kingdom, particularly as it relates to assessing a client's risk attitude. The FSA s rules have done little to help financial advisors better understand how they should measure someone's risk attitude or use a risk score when developing a client's financial risk profile. This lack of regulatory prescription has encouraged innovation within the financial advisory community, and in response, numerous commercial firms have entered the marketplace to help financial advisory firms estimate the general risk attitude of clients. It should be noted that the use of solutions created by these commercial firms does not, in the eyes of regulators, remove the professional responsibility of the advisor or firm in the determination of a client's risk profile.

Market research estimates that the international risk profiling market was worth £20m in the UK in 2015 (see subsection F 4.3). The revenues of the key players are closely guarded secrets due to their rivalry and the fact that few are publicly listed.

Key players in the risk profiling equipment marketplace include FinaMetrica, Dynamic Planner, and Vanguard, and Oxford Risk.

FinaMetrica risk tolerance system is a psychometric tool and has been adopted by leading advisers and private banks and brokers for over 10 years, the tool was developed with the Corporation of University of New South Wales.

Dynamic Planner is the UK's most widely used digital risk profiling and financial planning service, Used by more than 9,000 financial planners from over 700 firms according to their website[5].

Vanguard is one of the world's largest investment companies, offering a large selection of low-cost mutual funds, ETFs, advice, and related services they developed their own risk profiling system which consists of 11 questions for the porpoise of helping client assets among allocation among different asset classes (stocks, bonds, and short-term reserves). Vanguard does not charge you a fee to use their risk profiling questionnaire.

4.3 Case study introduction

The focus of this case study will be a risk profiling system developed by financial risk consultancy. The 'Gate 3 Scorecard for Project Selection' will be used to evaluate the commercial potential of the product.

Case Study – The In-house Risk Profiling System

[5] https://www.dynamicplanner.com/

A risk profiling system was developed within a financial risk consultancy firm as part of a new product exploration exercise. Due to the success of the exercise, there is a desire to understand the commercial potential of the product.

Case Study Method – Stage-Gate 3 Scorecard

A review of the NPD literature identified the 'Stage-Gate 3 Scorecard for Project Selection' (R. Cooper 2006, 2008) as a suitable evaluation method due to its grounding in empirical research. The Scorecard identifies six factors and 25 questions to elicit the presence or absence of success factors in a potential NPD project (see Table 4.1).

A. Strategic Fit & Importance
1. Alignment of project with business strategy 2. Importance of project to the strategy 3. Impact on business
B. Product & Competitive Advantage
1. Product delivers unique user benefits 2. Product offers user excellent value for money 3. Differentiated product in the eyes of the user 4. Positive user feedback on product concept
C. Market Attractiveness
1. Market Size 2. Market Growth & Future Potential 3. Margins earned by others in the market 4. Competitiveness – how intense competition is in the marketplace
D. Core Competencies Leverage
1. Product leverages competencies in technology 2. Product leverages competencies in production/operations 3. Product leverages competencies in marketing (brand, image, and communications) 4. Product leverages competencies in distribution & sales force

E. Technical Feasibility
1. Size of technical gap (straight-forwardness)
2. Technical complexity (barriers to achievement)
3. Familiarity with technology
4. Technical track record on this type of project
5. Technical results to date (proof concept)
F. Financial Reward vs Risk
1. Size of financial opportunity
2. Financial Return (Net Present Value / Expected Commercial Value / Internal Rate of Return)
3. Productivity Index
4. Certainty of financial estimates
5. Level of risk & ability to address risk

Table 4.1. Stage-Gate 3 Scorecard

Each of these six factors will be analysed in Section 6.4 to identify the commercial potential of the case study product. In this work, each factor will be rated on a three-point scale as low (1), moderate (2) or high (3), indicating the attractiveness of the NPD project with respect to each criterion.

4.4 Assessment of commercial potential

The overall commercial potential of the risk-profiling system was deemed to be 'moderate'. The evidence available suggests that the product has a 'high' competitive advantage; 'moderate'-to-'high' technical feasibility; 'moderate' strategic fit and market attractiveness, but a 'low' leverage of core competencies and a 'low' financial reward versus risk. The overall attractiveness was calculated using the arithmetic mean of these factors and can be seen in Table 4.2.

Success Factor	**Attractiveness**
Strategic Fit & Importance	Moderate (2)
Product & Competitive Advantage	High (3)
Market Attractiveness	Moderate (2)
Core Competencies Leverage	Moderate (2)
Technical Feasibility	Moderate-High (2.5)
Financial Reward vs Risk	Low (2)
Overall Attractiveness	Moderate-High (2.3)

Table 4.2. Score system

A. Strategic fit and importance

Overall the strategic fit and importance of this project can be considered 'moderate'.

A.1 The strategic fit of the risk profiling system is moderate.

The risk profiling system is broadly aligned with the organisation's current 2015/2016 strategy and it can be viewed to contribute towards the success of a specific strategic objective, which is the development of tools to attract institutional and retail clients.

A.2 The importance of this project to strategy is low.

Effort and importance are currently being focused on developing sophisticated risk models using network analysis and advanced forecasting techniques. The market risk profiling can feed into company dashboard, making it a complementary offering. However, at present it is not seen as central to the development of operational performance monitoring market risk.

A.3 The impact of this project to the business is moderate.

Impact is moderate because the financial reward is forecast to be modest ~£1.3 million over five years (see subsection F for further details). However, the product may have more value than its cash flow suggests because it can be used to develop an interest in higher-margin consultancy services where it could have a more significant impact.

The product will be launched under the current CheckRisk logo and we are currently researching the possibility of adding a University of Bath school association and logo into the product. We believe that this product will add to the company brand awareness. See Figures 4.1 and 4.2 for a detailed description of how the product fit into the company product line, after which costs and revenues are identified, along with the expected lifetime of the project, which is expected to be 5 years.

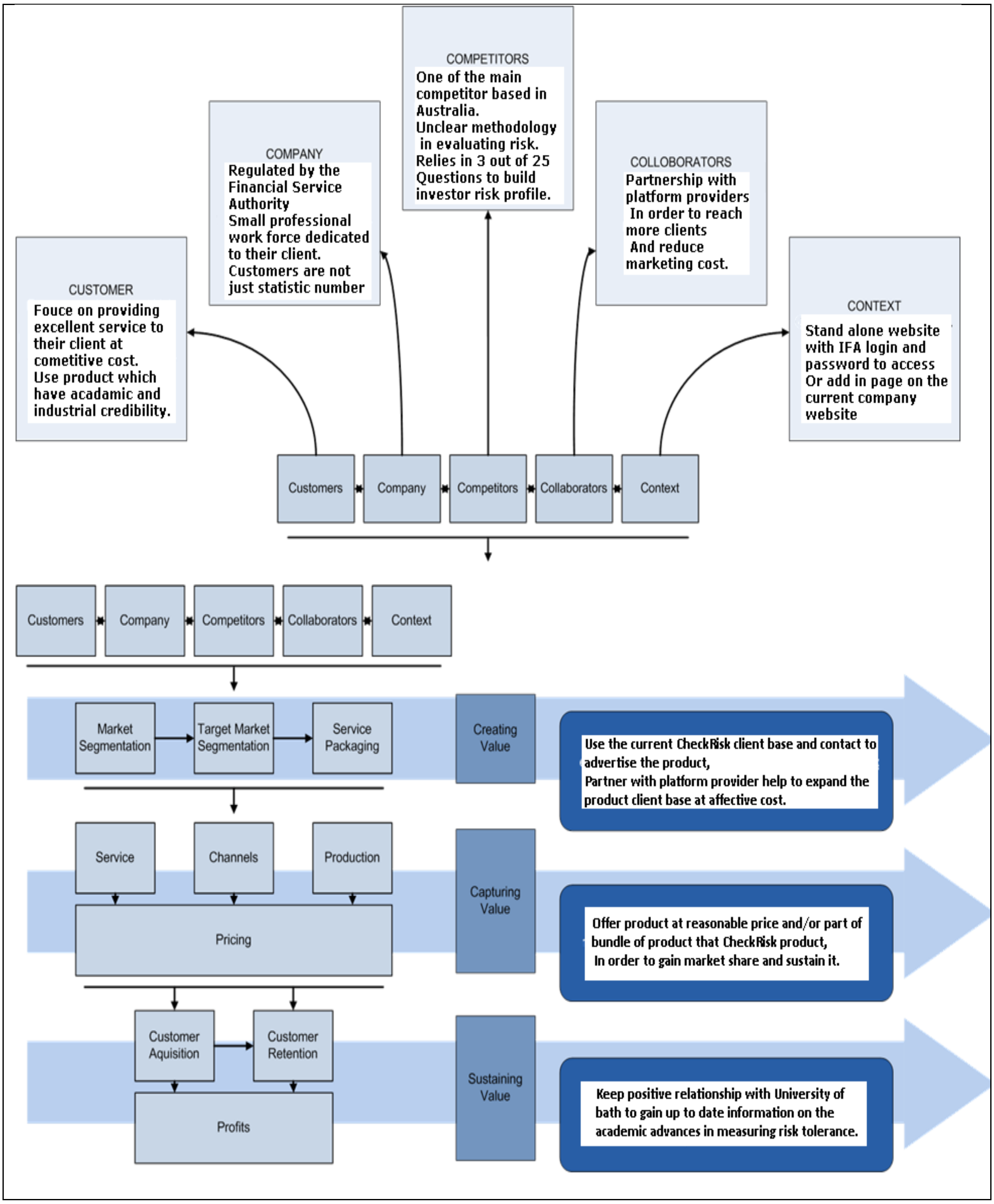


Figure 4.1 The diagram above shows how our product is positioned in view of customers, company, competition, collaboration and overall context.

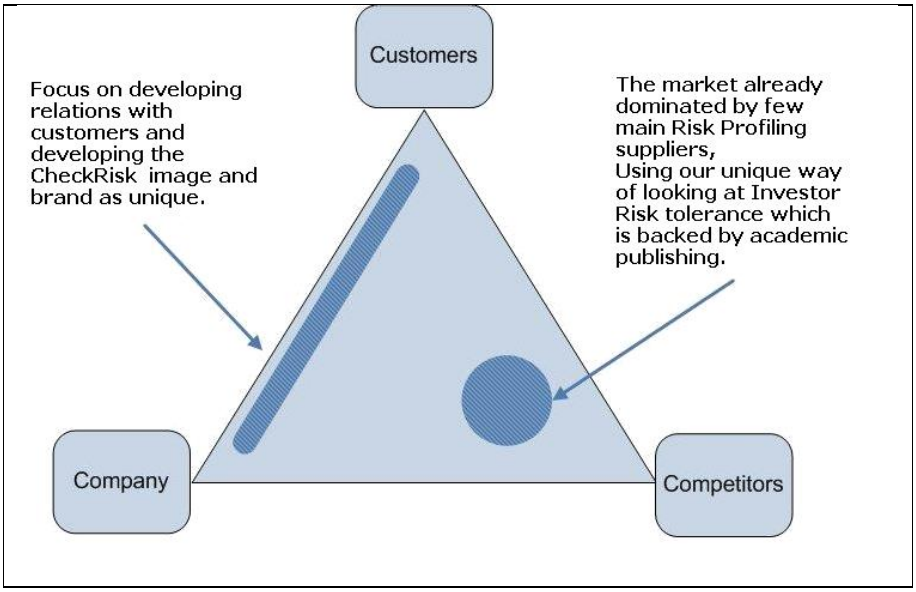


Figure 4.2 shows the positioning of our product in prospect of customer, company and competitors

B. Product and competitive advantage

The overall product and competitive advantage of this project can be considered to be 'high'.

B.1 The product delivers high levels of unique user benefits.

Our system is differentiated from its competitors in that it uses trading game simulator offers unique user benefits.

B.2 The product delivers high levels of value for money.

The product offers users excellent value for money in comparison to its competitors. It is a cheap but reliable option.

B.3 The differentiation from other products in the market is moderate.

Our model is user-friendly plain English, jargon-free, easily understood and answered through the questionnaire, technically rigorous, and offers to the client a personalised check of how they compare to others and how they compare to their partners.

The market for risk profiling is increasing as the financial conduct authority increases the pressure on businesses to ensure they gauge and communicate risk efficiently. The CheckRisk profiling system goes into more detail than some IFAs will have the appetite for, but for those that wish to demonstrate the value of a more comprehensive analysis, especially for high-net worth clients, it is a credible benchmark solution bolstered by a strong academic foundation.

C. Market attractiveness

The market attractiveness of the risk profiling system can be considered 'high'.

C.1 The market size can be considered high.

No data is currently available on the size of the UK risk-profiling market. As mentioned above, this is because revenues of the major companies in this area are closely guarded secrets and few are publicly listed. This work estimates the UK risk profiling market be worth £50m. See subsection F for further details.

C.2 The market growth and future potential of the risk profiling market can be considered moderate.

On the basis of the worldwide figures discussed in the background section, one can speculate that the UK market will grow moderately between 2014 and 2018. The evidence available suggests that large retailers have already adopted risk profiling technology and so we can expect growth in other areas such as the pension and annuity sectors.

C.3 The margins earned by others in the market can be considered moderate to high.

Whilst it is difficult to establish the margins of vendors in the marketplace since the majority are not publicly listed, one of the major players, Dynamic Profiling, stated in their annual cash flow statement their total revenues £5.3m up from £4.8m the year before (see Figure 4.3). The margin is assumed to be high once the system is fully developed and running.

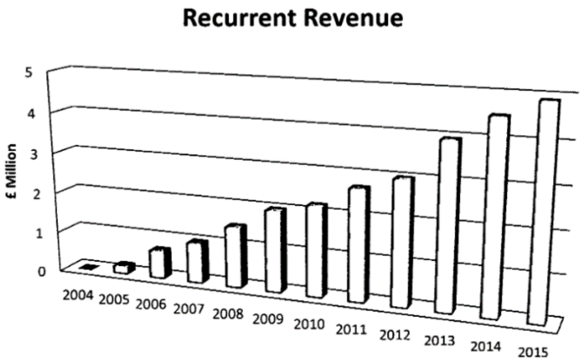


Figure 4.3 Dynamic planner showing Recurrent Revenue rising toward £5.3m in 2015[6]

C.4 Competitiveness of the marketplace is high (high is worse).

The worldwide risk-profiling marketplace is extremely competitive with a large number of established players. Much of this competition focuses on the financial advisory sector (Independent financial advisers). To avoid this intense competition, it is recommended to target niches such as Pension /Annuity providers – areas that this company already has strong links and clients.

D. Core competencies leverage

Overall the project has a 'low' level of core competency leverage. This product leverages a number of existing core competencies but also requires the development of new competencies in production and operations, marketing, sales and distribution.

D.1 The product leverage of technology competencies is low.

Existing competencies in software development and mobile App has to be leveraged.

D.2 The product leverage of production and operations competencies is low.

The product requires the development of a competency in building, installing, supporting and maintaining a software product. At present, the organisation is setup up to be a consultancy, therefore, there are no existing resources with commercial experience of these competencies. To narrow this competency gap, a partnership with an organisation with these core competencies may be desirable.

D.3 The product leverage of marketing competencies is moderate.

[6] Company House reference https://beta.companieshouse.gov.uk/company/04741529

The product builds on the existing organisation reputation as leading consultancy in risk management as well as its corporate brand for being experts in all aspect of market risk and behavioural finance. Unfortunately, the organisation does not have a reputation for being a product vendor. However existing communications channels with clients can be leveraged to create awareness of the product and in-house consultants can share their expertise for product development as well as recommend it to clients where appropriate.

D.4 The product leverage of competencies in distribution and sales are low.

The product requires the development of a distribution and sales force competency. At present, the organisation does not a have product sales and distribution capability since it specialises in bidding for and delivering consultancy projects.

E. Technical feasibility

The project has a 'moderate 'to 'high' level of technical feasibility.

E.1 The size of the technical gap is low because a working prototype has been deployed in-house. *E.2 The technical complexity of the product is low* (lower is better). *E.3 The familiarity with the technology is moderate* because the team does not have a long history of product development.

E.4 Technical track record and *E.5 technical results to date are moderate*, since there is a working system that has been trialled at the University of Bath but not trialled with end-users.

F. Financial reward vs risk

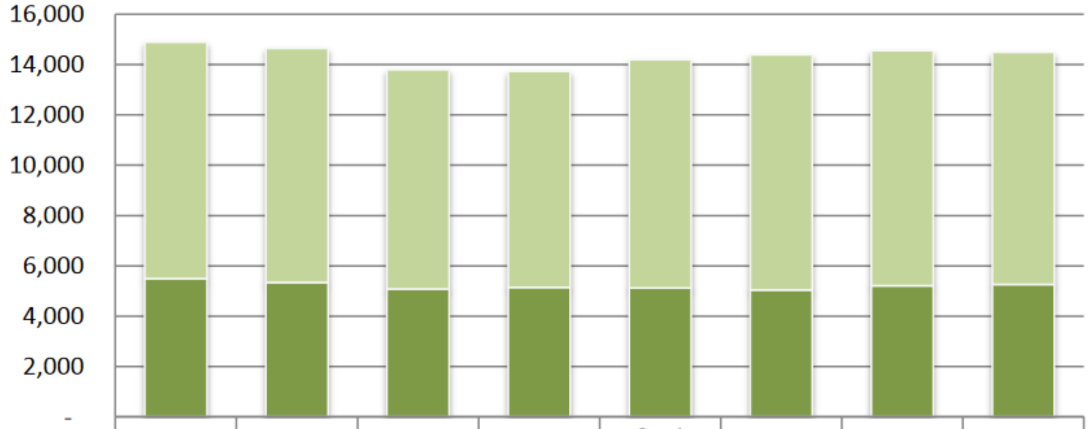
Overall the project has a 'high' reward vs risk profile. This is because although the project is low risk, the financial returns are also high.

F.1 The size of the financial opportunity can be considered moderate.

This is based on an estimate of the targeted market segment as being worth £1.5m on the basis of 24,000 target customers, a 1% penetration rate, and a £6,000 average customer spend.

We calculated this value by assuming that our target customers are UK IFA/Annuity providers. The total number of financial advice firms registered with the FCA as at 31 December 2015 was 14,491, a small decrease from Dec 2014 (see Figure 4.4). The number of staff working in financial advisory was 23,864 (in Dec 2015) a small increase from the year before (see Figure 4.4 and 4.5).

FinaMetrica is currently charging £800 per adviser making the UK market size (23,864*£800~ £20m).



	Dec 2008	Dec 2009	Dec 2010	Dec 2011	Sept 2012	Dec 2013	Dec 2014	Dec 2015
Total	14,884	14,648	13,791	13,732	14,189	14,387	14,550	14,491
Appntd reps	9,392	9,314	8,707	8,590	9,066	9,351	9,336	9,228
Directly auth	5,492	5,334	5,084	5,142	5,123	5,036	5,214	5,263

Figure 4.4. Number of registered IFAs in the UK

Figure 4.5 shows the number of advisers registered with FCA

We estimate the size of the UK pension market to be £2.4 trillion at the end of December 2015. Figure 4.6 and 4.7 includes all assets in DB and DC pensions, as well as those assets in some form of drawdown or assets backing annuities. As we can see the size of the market is huge and using the ABI data (see Figure 4.6, 4.7) we can estimate the annual the annual sale of 83,000 annuities in 2015.

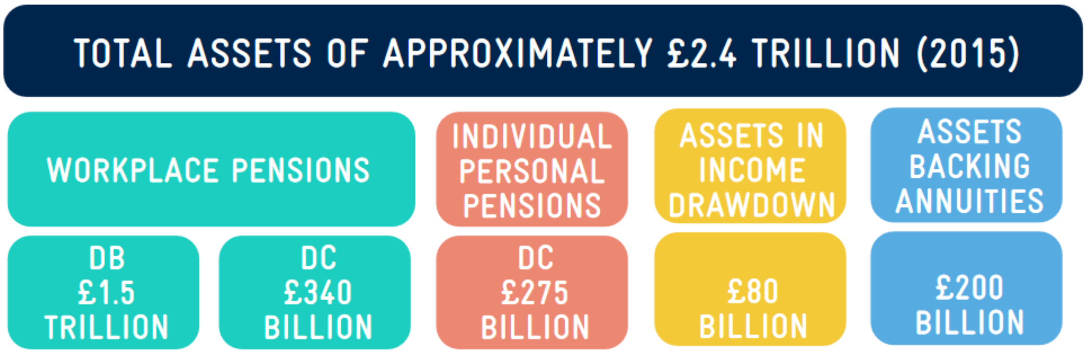


Figure 4.6 shows the size of the UK pension industry

2015 Data	Q2 2015	Q3 2015	Q4 2015	Total- nine months since reforms
Annuity sales	£990m invested in around 18,200 annuities, making the average fund invested just over £54,500.	£1.17bn invested in around 22,380 annuities, making the average fund invested just over £52,300.	£1.1bn invested in around 21,200 annuities making the average fund invested nearly £51,900	£3.3bn invested in around 61,700 annuities, making the average fund invested nearly £53,000.

Figure 4.7 Shows annuity sales in the UK in 2015 (from Association of British Insurance[7])

We estimate the number of target customers to be ~30,000 on the basis that we are targeting all UK IFA and pension/annuity advisors. Thirdly we estimate a market penetration rate of 1% on the basis that in the IFA business is already dominated by two large players. Fourthly we estimate market value by using:

Market Value = Market Size x Penetration x AVG Price

F.2 The financial return over a 5-year period is moderate.

The financial return was calculated using Net Present Value (NPV). As can be seen from Table 4.3 below, an NPV of ~£1.4m can be expected after five years assuming a discount rate of 4% and modest sales figures that are assumed to be representative of what would occur without an aggressive sales growth strategy.

[7] (https://www.abi.org.uk/News/News-releases/2016/03/ABI-pension-freedom-statistics-one-year-on-factsheet)

Year	Net Cash flow	Net Present Value	No Sales	AVG Sale Price	AVG Cost Per Sale
0	-£50,000.00	**-£50,000.00**	0	5,000	2,500
1	£10,000.00	**£65,569.53**	50	5,000	2,500
2	£20,000.00	**£176,694.07**	100	5,000	2,500
3	£30,000.00	**£283,544.60**	150	25,000	2,500
4	£40,000.00	**£386,285.48**	200	25,000	2,500
5	£50,000.00	**£1,374,178.64**	250	5,000	2,500
Discount Rate			4%		

Table 4.3 Expected financial return over five years.

NPV was calculated using the equation below:

NPV (i,N) = $\Sigma R_t / (1+i)^t$

Where i is the discount rate, N total number of time periods, R_t is the return at time t. We also make the following assumptions to generate an estimate of financial returns: i) An initial £50,000 cash investment is made in product development, launch and marketing activities; ii) Average Sale Price of £5,000 for IFA; iii) Average Cost Per Sale of £2,500; iv) Linear growth over 5 years; v) Discount rate of 4%.

F.3 The productivity index of the project is unknown.

This is because there is no historic data on the team commercialising products and thus the productivity index score cannot be calculated due to the uncertainty of the number of person-days required to complete the project. If data were available, productivity could be calculated as follows:

Productivity Index = Output / Input = NPV / Person-Days

F.4 The certainty of the financial estimates is low.

It is important to note that there is significant uncertainty due to the uncertainty associated with the market size, penetration and average customer spend. However, a set of reasonable assumptions was made to understand the order of magnitude of the financial rewards vs the risk.

F.5 The level of financial risk in pursuing this product is low given the ballpark costs suggested above.

However, it should be noted that the estimated net cash flow is unlikely to be large unless an aggressive growth strategy is pursued which would then increase the risk of the project due to increases in resource investment.

It is recommended that this project is considered alongside a portfolio of other prospective projects, so investment decisions can be made on the basis of portfolio metrics, such as their return on investment and comparative productivity index.

4.4 Exit strategy

Following successful trading in the UK, CheckRisk is planning to expand to the US and Australia where it has already established a client base in the wealth/pension asset management business consultancy. Furthermore, we are planning to operate the system in several languages. The wealth of data which will be acquired can be used for academic propose to add understanding into the behavioural trends and risk attitude.

The direct revenue from the product is estimated not to be high initially, but we believe that it will help to establish our company as a leading market risk consultancy, adding to the portfolio of services our company provides.

Once launched, the product itself doesn't require an intensive support team, and any further development on the product can be done easily and cheaply. See Figure 4.8 for a typical exit scenario.

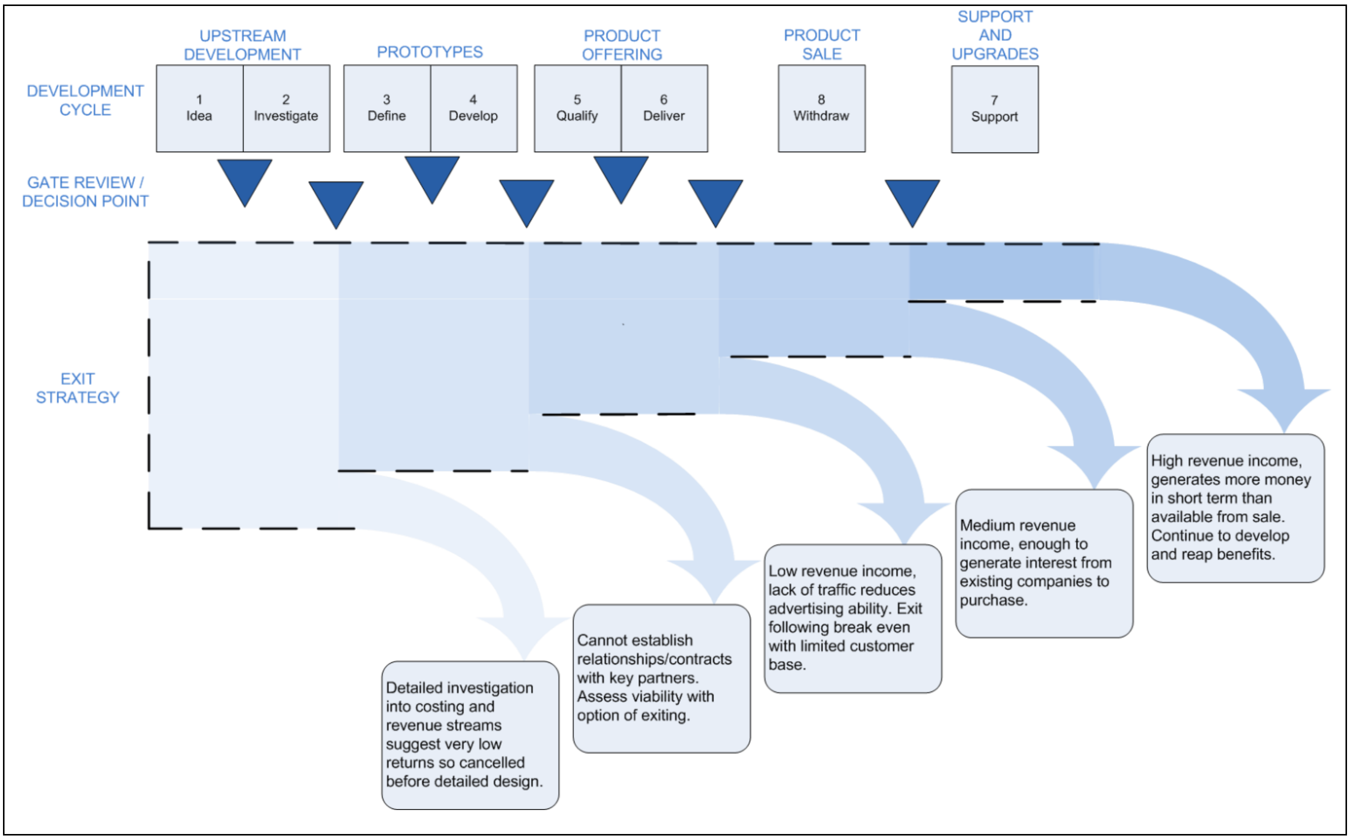


Figure 4.8 shows a typical exit strategy (CheckRisk is currently on the product offering stage)

4.5 Risk tolerance questionnaire platform design

It is important to begin any discussion of risk profiling by acknowledging that an individual's risk profile is assumed to be a combination of objective and subjective attributes consisting of a set of relatively stable parameters financial advisors should consider when helping their clients evaluate risky financial choices.

Objective factors are those elements that can be measured quantitatively. Examples include an individual's capacity to incur financial losses and the time horizon associated with the accomplishment of a financial objective. Subjective factors include concepts such as risk perception and risk preference, both of which are based on a client's idiosyncratic evaluations of the riskiness of a situation or choice.

Hence our questionnaire draws on behavioural and quantitative inputs using a subjective questions section, an investment "game" and a quantitative section. The idea is to establish a client's risk tolerance and to collate data over time which will drive further iterations of the questionnaire.

One of the outputs of the risk profile will be a score of 1-100 that classifies investors into seven groups according to their risk tolerance. Risk Group 1 is the least risk averse/most risk tolerant, and Risk Group 7 is the most risk averse/least risk tolerant (see Figure 4.9).

Risk Group						
1	2	3	4	5	6	7
1-15	16-30	31-45	46-60	61-75	76-90	91-100
				XXXXX		

Figure 4.9. Shows the risk group output from the CheckRisk profiling system

Who is the customer?

Independent financial advisers (IFAs) can be a 'one stop shop' for all of his/her client's financial needs. The adviser's main responsibility is to understand what is going on with his client's life and develop a business plan depends on his/her needs (see Figure 4.10).

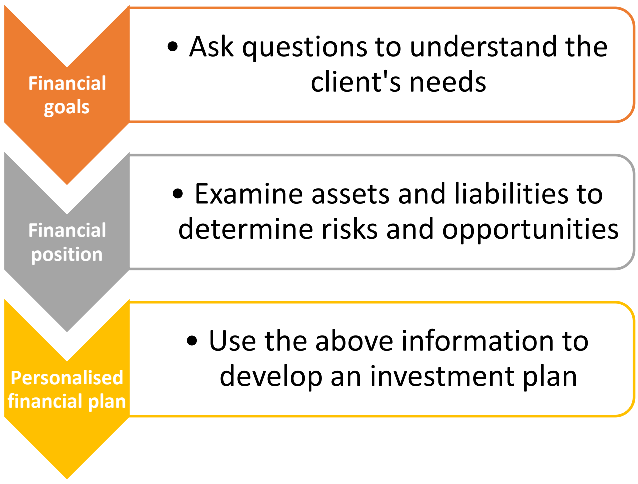


Figure 4.10 shows a typical workflow of an independent financial adviser

Clients have to update their financial advisers in any change in their financial circumstances, so a six-month financial plan rear-view is always recommended. The financial adviser fee structure is either flat fee/hourly rate e.g. £200/hour or a percentage of the asset under management e.g. 1% annual fee.

There are three key facts that the financial advisers need to know about their client before making any informed decision: hard facts such as value of income, debts, and assets; soft facts such as their attitude, feeling and risk tolerance; and firm facts such as their future commitments and goals.

Platform Design

1. Introduction

The risk-profiling system takes around 10 to 15 minutes to complete. The questions are clearly structured, and the usability of the system is high. CheckRisk believes that investors would be happy to spend 10 to 15 minutes to ensure their investment portfolios matched their risk tolerance (see figure 4.11).

The full MATLAB code to generate the platform is included in Appendix 11.

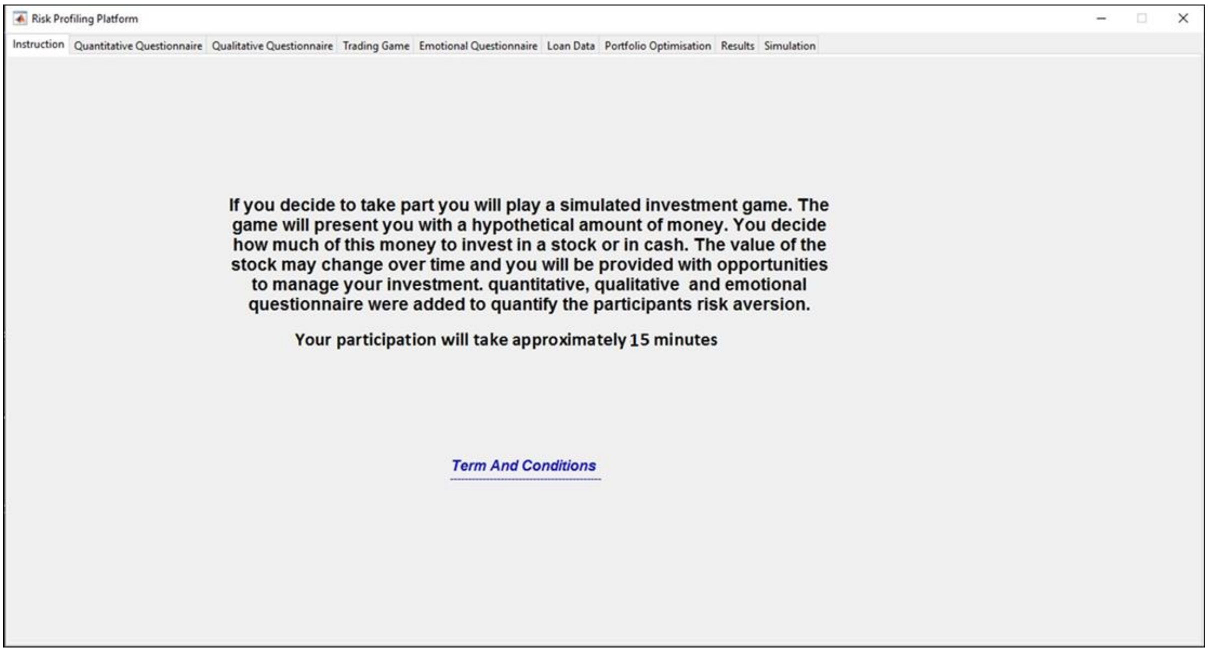


Figure 4.11 Shows layout of the platform design containing 9 tabs

(Tabs are 1. Introduction, 2. Quantitative questionnaire, 3. Qualitative questionnaire, 4. The trading game, 5. The emotional questionnaire, 6. Load Data, 7. Portfolio optimization, 8. Results, 9. Simulation)

2. Quantitative Questionnaire

The first part of the questionnaire is the quantitative section, where the investors are asked to answer a prospect theory-type question to measure client risk tolerance (see Figure 4.12). To measure risk tolerance, CheckRisk uses 16 qualitative questions, an investor game, and seven quantitative questions. It is worth noting that the numbers of questions we are using is noticeably more than the majority of risk profiling systems. CheckRisk uses more questions firstly to increase the accuracy and consistency of the outputs, but also to gain more soft information to help the IFAs build a clearer picture of the client. CheckRisk believes that using more questions and trading game watered down the effect of a specific answer being influenced by a particular experience, the frame of mind or miss-interpretation.

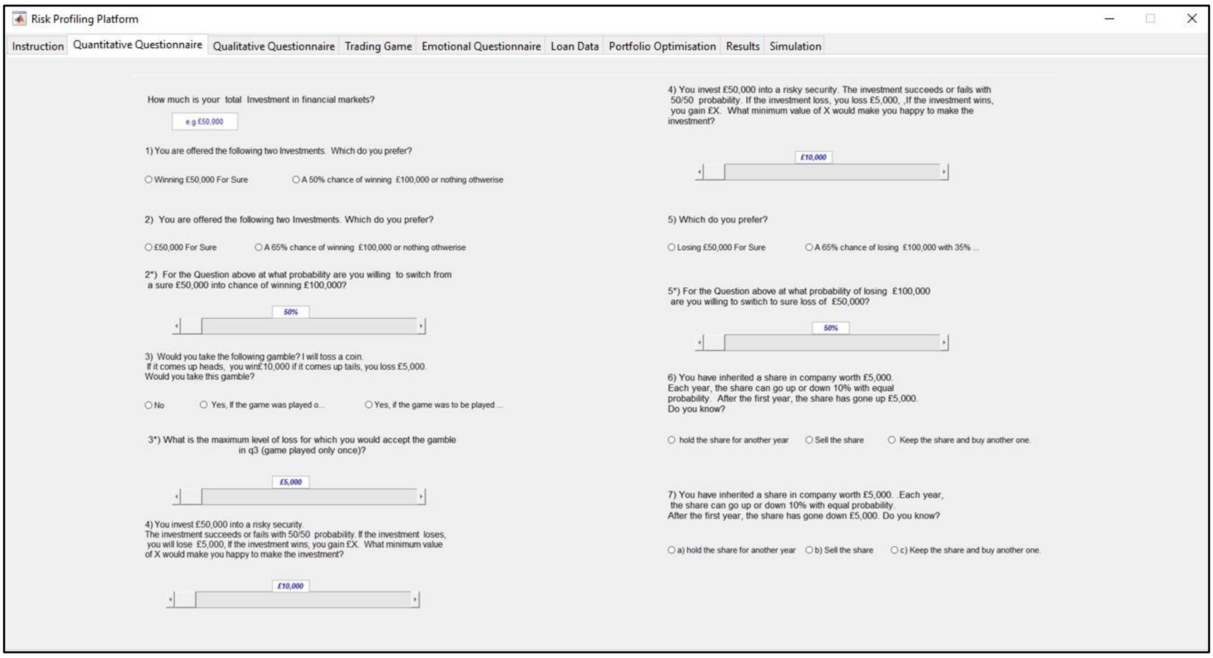


Figure 4.12 Shows the 7-question quantitative questionnaire

3. Qualitative Questionnaire

While the majority of financial advisers are busy acquiring 'hard' data, the 'soft' facts are usually overlooked, in spite of their importance to forming the advice needed. CheckRisk started building its risk-tolerance profiling system with the help of a University of Bath Doctor of Engineering Student to analysis the risk tolerance of investor/market participants (see Figure 4.13).

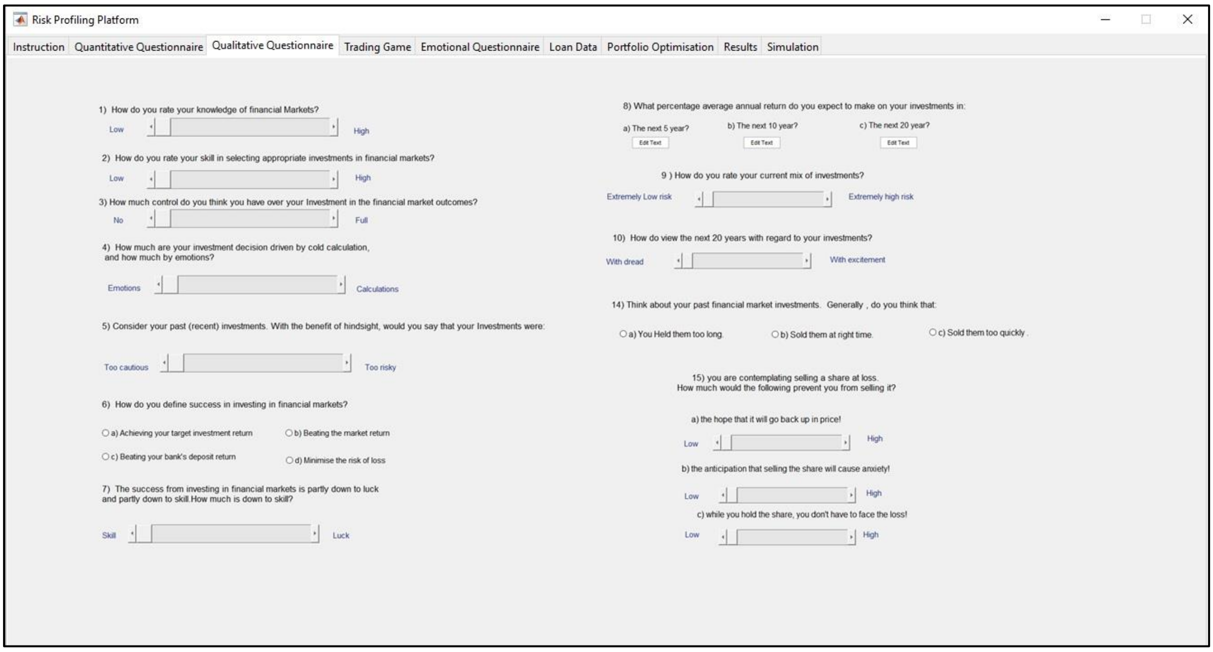


Figure 4.13 Shows the 15-question qualitative questionnaire

4. Risk game

One of the unique selling points of the CheckRisk risk-profiling system is the investment 'trading game' where we ask the client to trade between stock and cash under different market scenarios:

*"You inherited £20,000 last year, and you have been asked to invest this money in cash and stocks (equities). At the start of the year, you invest equal amounts of £10,000 in both stocks and cash. The performance of the equity fund is plotted below (*see Figure 4.14*). You have been asked to manage your portfolio by allocating your money between stocks and cash, making the decision at the end of each investment year. Note the cash allocation grows by the risk-free interest rate of 2%."*

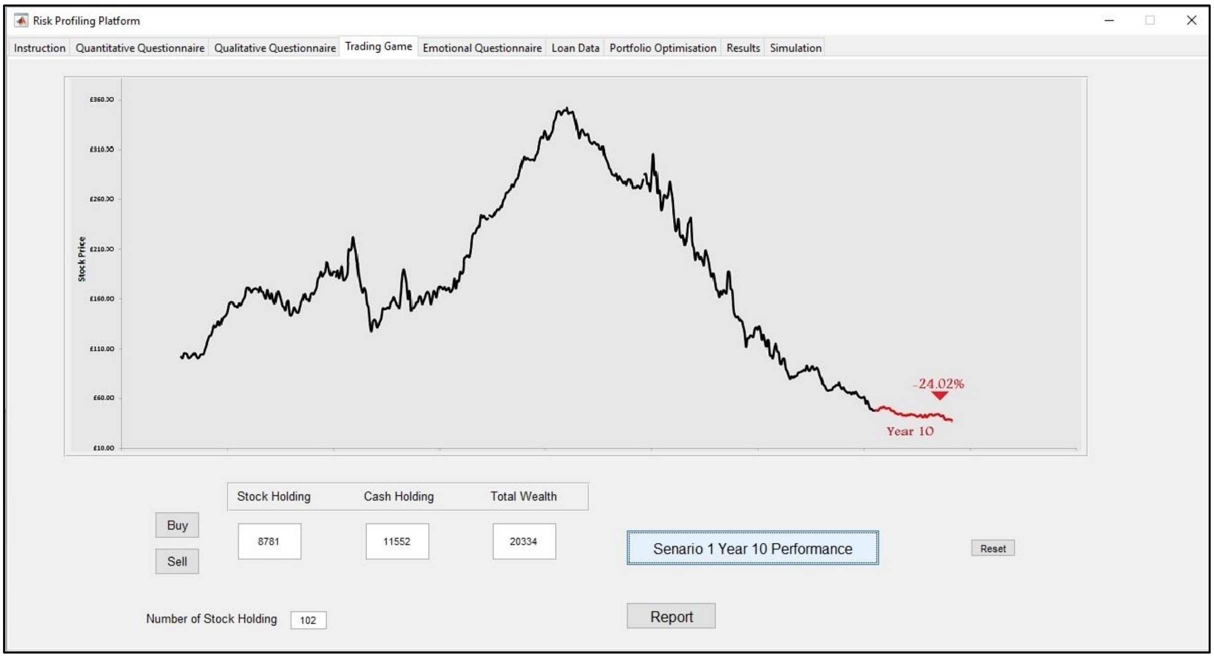


Figure 4.14 The Trading Game layout

We also observe their trading performance from risk/return context and trading activity and strategy (see Figure 4.15).

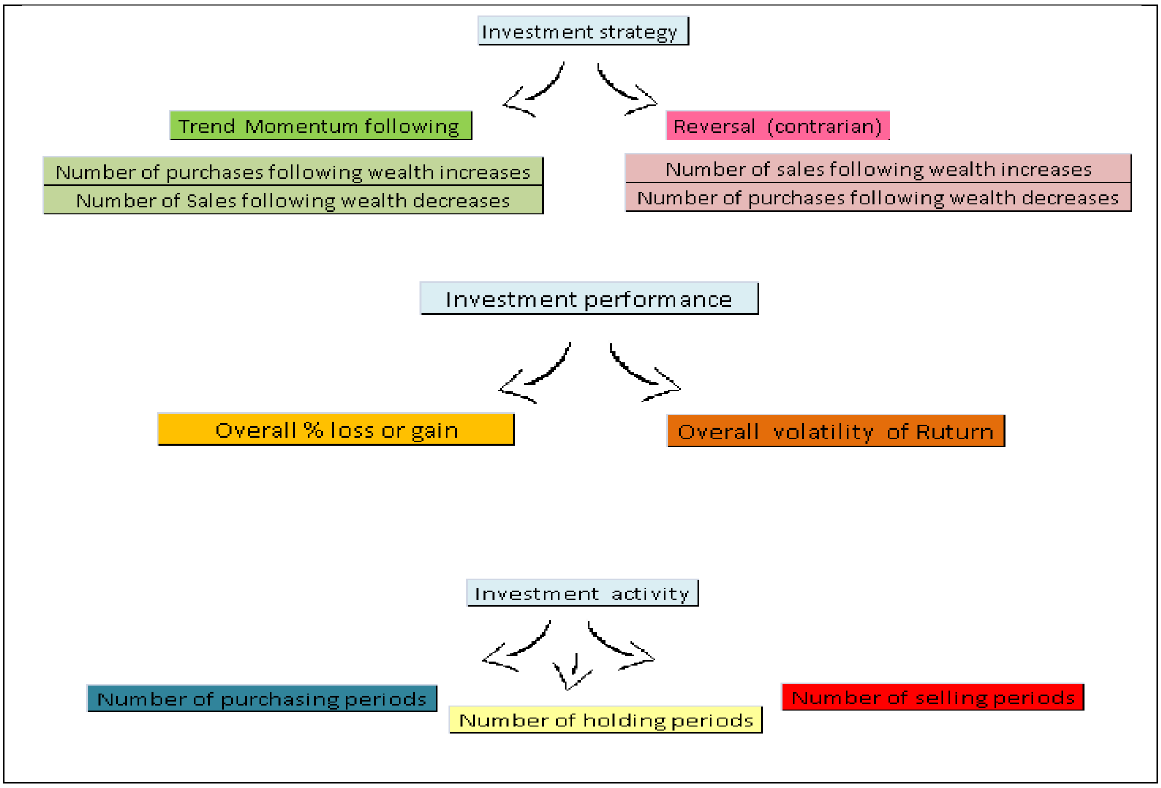


Figure 4.15 Shows the output observed from the trading game

5. Emotionality Assessment

There are verified techniques using psychometrics that improve the measurement of some subjective or emotional factors like risk tolerance or loss aversion, but they are rarely used by the industry. In the CheckRisk profiling, we ask the investor to report the intensity of each emotion they experience during the game (see Figure 4.16).

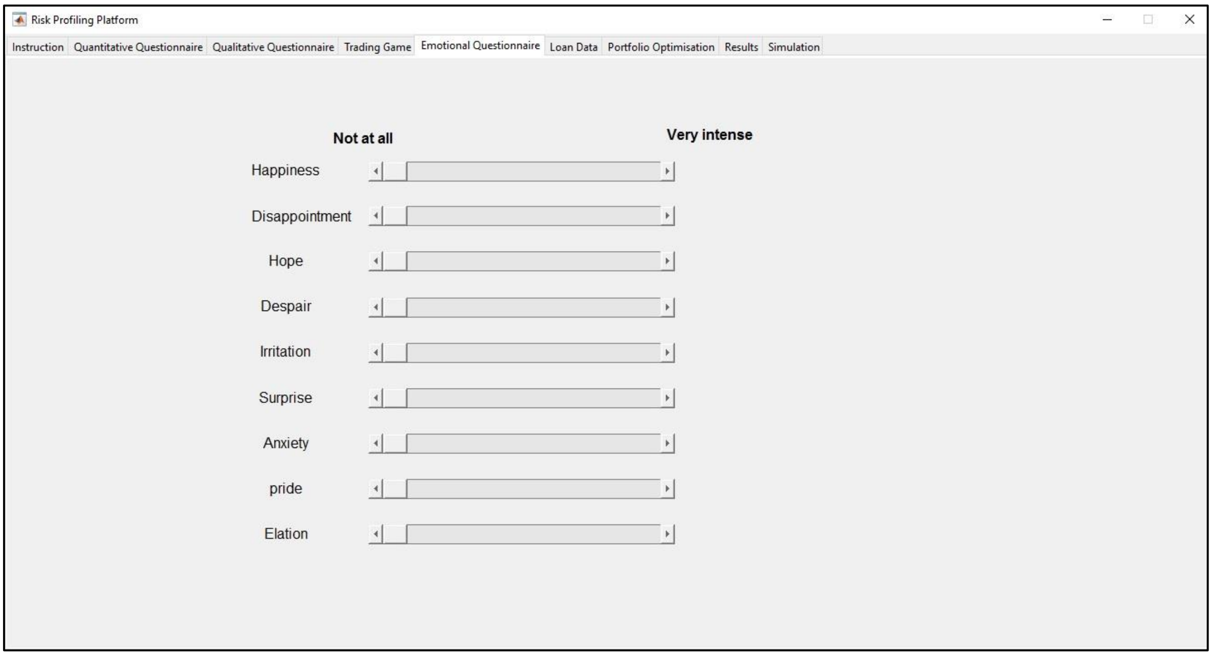


Figure 4.16 Emotional Assessment questionnaire used in the platform

6. Upload a pool of assets to be considered in the client portfolio

CheckRisk also considers developing sales aids for a financial adviser to help them convert the output of the system into recommendations regarding asset allocation i.e. it provides the recommended percentage of financial assets that should be used for each risk group (this is not a definitive percentage, but displays the acceptable or unacceptable range for the portfolio constructions. See Figure 4.17 for the adviser's upload of a pool of assets from a database or data feed (e.g. Yahoo, Bloomberg) to create a universe from where they can build a portfolio.

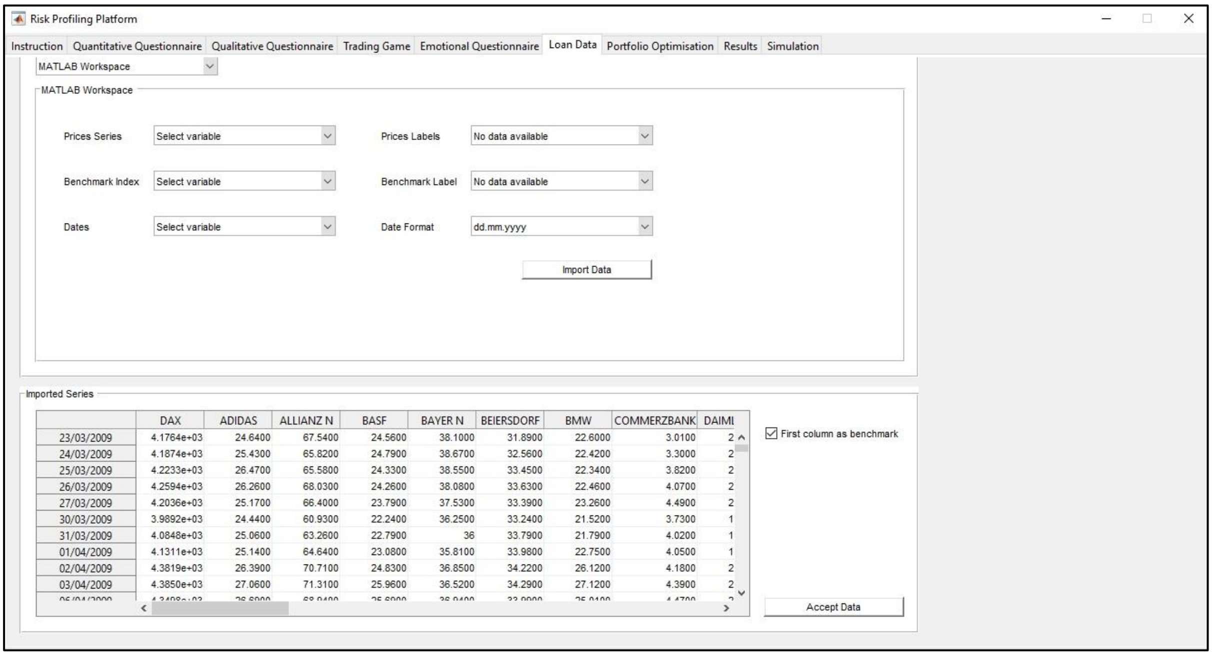


Figure 4.17. Uploading of data for portfolio selection

7. Apply portfolio constraints

The platform also gives the option to either log return or exponential return, which add weight to the most recent returns. We can apply a constraint on the portfolio allocation (see Figure 4.18).

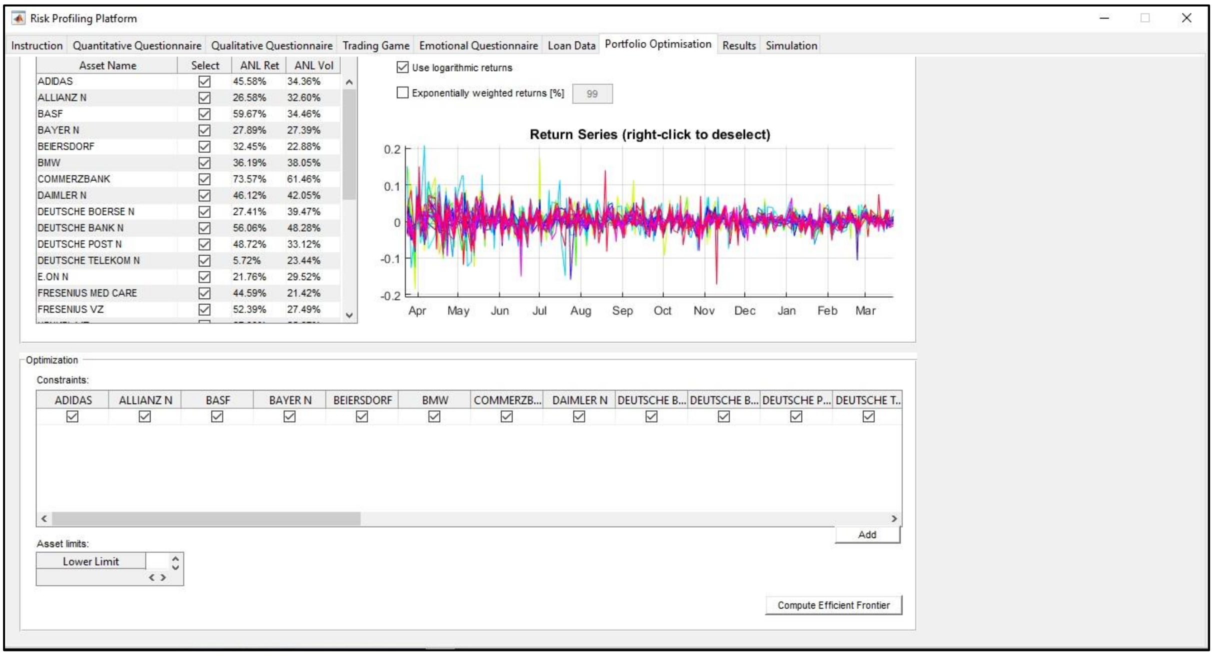


Figure 4.18. Applying portfolio constraints

8. Results

One of the factors to consider when selecting the optimal portfolio for a particular investor is the degree of risk aversion. This level of aversion to risk can be characterised by defining the investor's indifference curve. This curve consists of the family of risk/return pairs defining the trade-off between the expected return and the risk. It establishes the increment in return that an investor requires to make an increment in risk worthwhile. Typical risk aversion coefficients range from 2.0 through 4.0, with the higher number representing lesser tolerance to risk (see Graph 1). The equation used to represent risk aversion is:

$U = \overline{X} - (r+e)\sigma^2$ here:

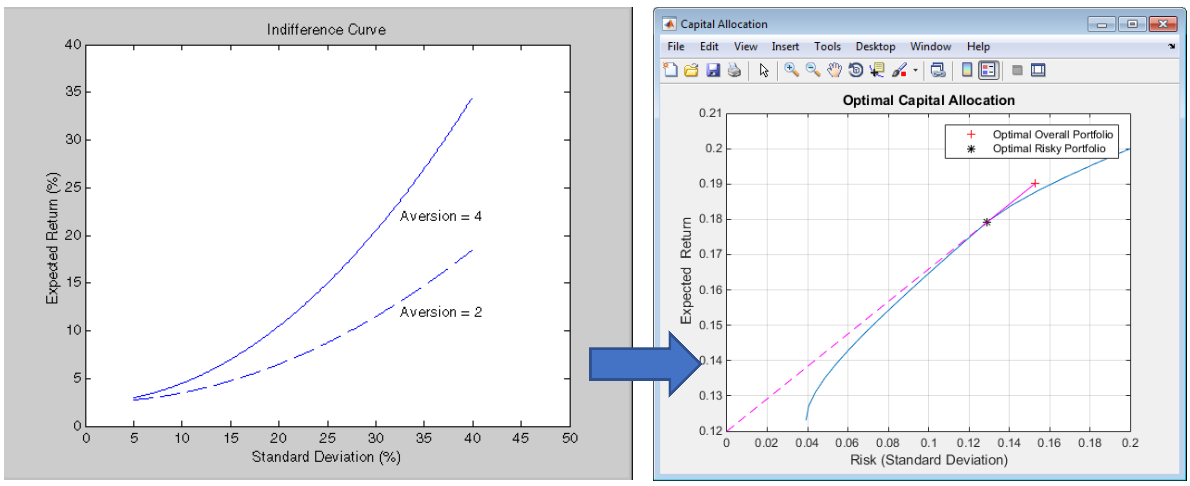
U is the utility value.

X is the expected return.

r is the index of investor's aversion.

E is the index of investor's emotionality

σ^2 is the standard deviation.



Graph 1: An investor's indifference curve

This example computes the optimal risky portfolio on the efficient frontier based on the risk-free rate, the borrowing rate, and the investor's degree of risk aversion.

The overall portfolio combines investments in the risk-free asset and in the risky portfolio. The actual proportion assigned to each of these two investments is determined by the degree of risk aversion characterising the investor.

We use the Hanna et al (2001) utility function from our experiments to obtain the coefficient of risk aversion. So, we would say that this is the utility function to use to develop an individual's coefficient of risk aversion.

Then, for portfolio analysis, we would need to input the coefficient of risk aversion into the expected utility function. We would then be able to get the optimal allocation of wealth to risk-free and risky. Our contribution would be to also add in emotions from the experiment. Figure 4.19 visualises the optimal portfolio that matches the client's risk aversion.

Figure 4.19 Shows the output of the portfolio optimisation

9. Portfolio simulation

Our portfolio simulation provides a historic look at the portfolio performance for difference risk groups, displaying the corresponding volatility, expected return, value at risk, and expected shortfall for each risk group based on historic performance of the portfolio. The tool is useful in setting clients' expectations and helps to test whether they have the correct risk profile (see Figure 4.20).

Figure 4.20 shows the portfolio simulation output layout

The portfolio has five methods of analysis projection:

1) Monte Carlo simulation

2) Bootstrap

3) Copula

4) Regime switch model

5) Filtered historical simulation

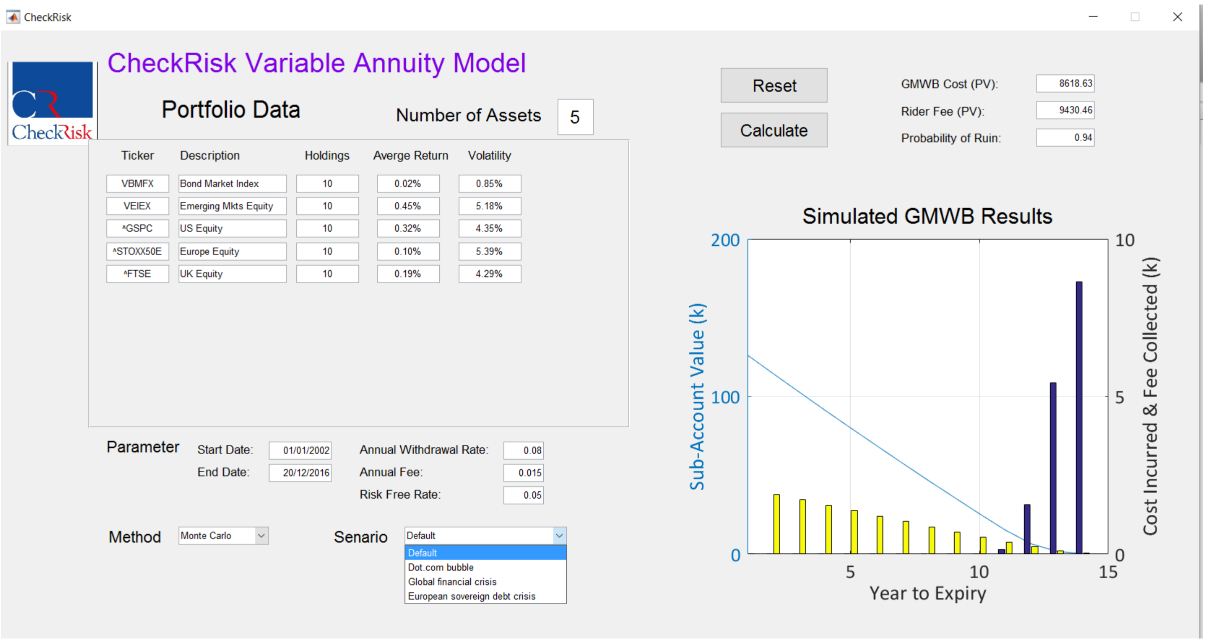
In addition, there are three historical simulations:

1) Dot.com bubble

2) Global financial crisis

3) European sovereign debt crisis

Moreover, it can be adopted for annuity or pension-planning by specifying the number of holding, free interest rate, annual withdrawal rate, and the annual charge fee. The platform then calculates the present cost of the contract, rider fee, probability of ruin and simulations of the subaccount value, fees collected, and costs incurred, which are all visualised over the length of the insurance (see Figure 4.21 and 4.22).



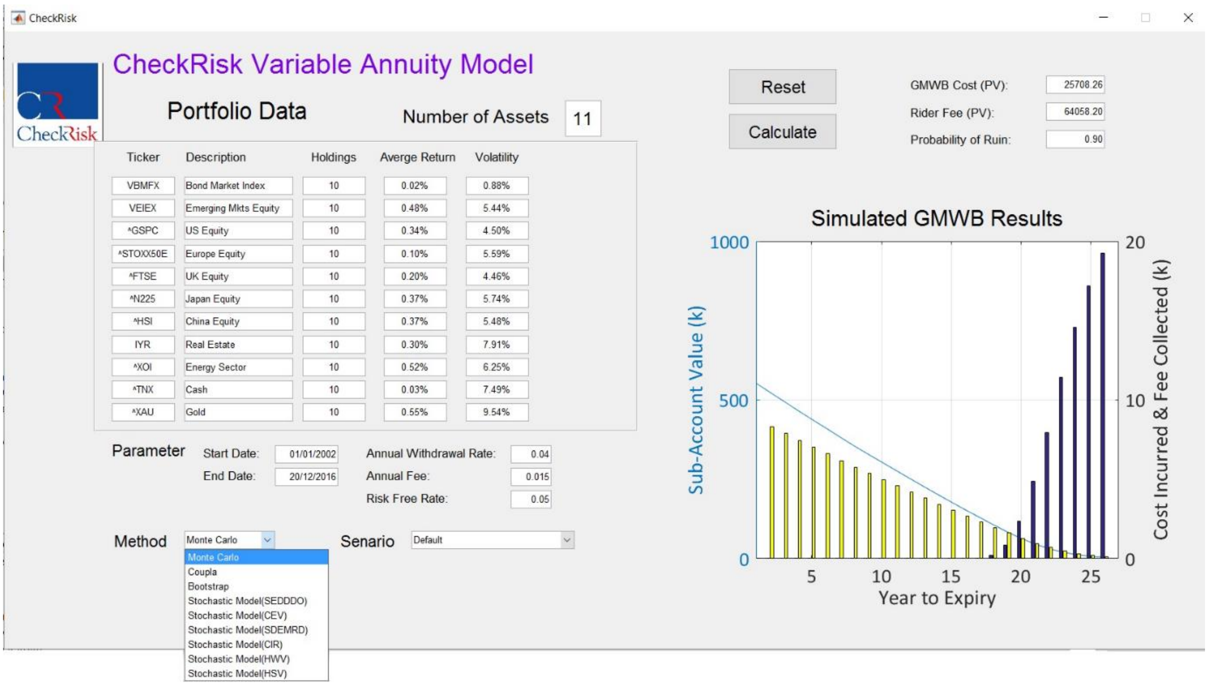


Figure 4.21 and 4.22. Screenshots of product customization for the annuity selection platform

4.6 Conclusions

Regulators worldwide have taken steps to introduce policies, rules, and regulations that require financial planners and other advisors to comply with minimum acceptable standards of practice when providing investment advice to no institutional clients, and one of this advisor role is to evaluate a client's risk profile and/or risk tolerance, which is broadly defined as a person's emotional and financial capacity to take on risk

The UK Financial Service Authority (FAS) was very vocal in a 2011 paper on Risk and Suitability[8] that it is concerned that financial advisers may take the output of a risk-profiling tool and apply the results without further deliberation. Our risk-profiling system openly encourages debate with the clients about their attitude to risk and what this means in form of asset allocation.

Risk profile is assumed to be a combination of objective and subjective attributes consisting of a set of relatively stable parameters financial advisors should consider when helping their clients evaluate risky financial choices.

Objective factors are those elements that can be measured quantitatively. Examples include an individual's capacity to incur financial losses and the time horizon associated with the accomplishment of a financial objective. Subjective factors include concepts such as risk perception and risk preference, both of which are based on a client's idiosyncratic evaluations of the riskiness of a situation or choice.

The output of the system is a risk score from 1-100 which compares the investors risk tolerance to that of the broad population, with fifty being the most normal output.

The system reports the investors' scores and categorises them into one of seven risk bands. It then continues to evaluate how the answers given compare with peers within the group for different views on risk tolerance, these include making financial choices and reacting to financial disappointments. This practice enables the IFA to identify anomalies in the answers and induces discussion about their attitude to market risk.

The reasons this product is useful for platforms and IFAs and pension advisers are:

- It provides a consistent, academically rigorous format for assessing client risk tolerance

[8] Assessing suitability: Establishing the risk a customer is willing and able to take and making a suitable investment selection https://www.fca.org.uk/publication/finalised-guidance/fsa-fg11-05.pdf

- It provides proof of 'Know your client' and a risk-based assessment of clients
- It assists IFAs in classifying an appropriate investment program
- It is updateable, so as time moves on IFAs can reassess their clients' needs
- It is a great way to show the regulator that Retail Distribution Review (RDR) is being taken seriously and provides a trail of reports to show that appropriate risk assessments are being made.

Finally The 'Stage-Gate 3 Scorecard for Project Selection' has demonstrated itself to be a useful method of rapidly evaluating the commercial potential of emergent products. The Stage-Gate 3 Scorecard is particularly well suited because the organisation can then go on to follow the Stage-Gate process until launch, thus ensuring it follows 'best practice' guidelines throughout the commercialisation process.

Chapter 5 Analysing Financial Herding Through Network Analysis

5.1 Summary

Emotional finance introduces the notion that financial markets may be driven by the co-existence of fully-rational and emotional investors, driven by fantasy. The analysis of emotional finance is informed with reference to a Freudian psychoanalytical framework.

In this chapter, we add to the existing information cascade and herding research by developing an emotional finance model that examines the effects of fantasy investors on the decisions of rational investors under dynamic pricing. We consider a financial market for a risky asset in which traders' emotions develop over time based on how they perform. We hypothesise that emotions affect traders' behaviour in a number of ways either love or hate, were love results in investors buying and holding their stock regardless of the realised profit or loss.

The assumptions of the model include a constant population size of investors**,** and that all individuals are identical in their susceptibility to various emotional states, we also assumes that the probability of becoming in love with stock is independent of an individual's history of emotional episodes and mood. We introduced an elementary agent-based asset pricing model consisting of three trader types: fundamental traders, emotional traders, and semi-emotional traders. The model comprises two features: 1) an emotional herding mechanism based on the susceptible-infected susceptible (SIS) model, and 2) wealth price herding based on wealth preferential attachment. We did this by creating set of investor' with their attributes and behaviours. Then we A set of investor relationships and methods of interaction: An underlying topology of connectedness defines how and with whom agents interact. Then the Market network were investor interact with their environment in addition to other investor.

Combining analytical and simulation methods, the interaction between these elements is studied in a four-phase plane of the price movement: 1) prices resembling a bull market; 2) prices resembling a bear market; 3) U-shaped pricing trends; and 4) n shaped pricing trends.

Finally, we compare our approach with a traditional information cascade/herding model incorporating fantasy investors.

We have formally demonstrated that emotions can be thought of as infectious diseases spreading across social networks. We have introduced a novel form of mathematical infectious disease model

for describing the spread of emotions .We have validated this model by studying emotional propagation between different group of investors across a social network.

5.2 Introduction

The EMH states that investors are rational and trade without any emotional input, so prices reflect all available information at all times. An alternate view is presented by Shefrin (1999), who introduces human emotions back into the equation. Shefrin writes that trading is not a solely calculating endeavour, but is subject to emotional impulses, such as greed, fear and other basic (and complex) human emotions.

It can be argued that all human decisions are emotional, not rational, in nature and there are many examples that violate EMH theory, from disappointment aversion (Gul, 1991) to regret theory (Bell, 1982) and prospect theory (Kahneman and Tversky, 1974 and Tversky and Kahneman, 1992). Taffler and Tuckett (2005) have started a major paradigm shift with the development of emotional finance, this ground-breaking new paradigm uses Freud's theory of phantastic objects as an explanation for unconscious and infantile emotions that affect investor decisions (Fairchild, 2009). Emotional finance theory argues that entire markets, as well as individual stocks, can be analysed with the subconscious emotions that result from the belief in phantastic objects (Tuckett, 2011). Market euphoria and a subsequent crash can be viewed in terms of the emotions associated with phantastic objects. The theory has been applied to the internet mania of the late 1990's – in which tech stocks were argued to represent the phantasies of the people holding them (Taffler & Tuckett, 2005). Emotional finance has also been applied to the rapid growth and dramatic decline of the hedge fund industry – hedge funds, it is argued, have become phantastic objects for people, mesmerized by stellar gains - and the people that run them are almost deified – that is, until reality sets in and mounting losses and liquidation transform the euphoria into anger and blame (Eshraghi & Taffler, 2009).

Therefore, investor irrationality – driven by human emotions – cannot be overlooked when financial decisions are made. To effectively model herding behaviour, it is of critical importance to give considerable weighting towards factors that allow for people's emotional impulses.

The development of communication technology and internet increased connectivity among Investors, were information and sentiment can transfer among market participants which in some incidents can lead to herding and asset price bubble, these sentiments, rumours, and opinions spread over networks of contacts between investors and market participants. Understanding the intrinsic mechanism behind Herding and emotional cascade in networks is an important task.

In this chapter, we adopt the susceptible-infected susceptible (SIS) model. The SIS model is one of the simplest models in epidemiology and is also known as the contact process model to model emotional cascade and we use network preferential attachment to model herding.

Here, we introduce a novel approach for studying the spread of emotions in a social network. We can think of emotions at two levels: 'Love/ positive' and 'Hate/ Negative'. We modify a classical infectious disease model to represent the spread of emotions, to account for the fact that emotions can be contracted both spontaneously and through transmission.
For an emotional state such as Positive/in love to fit the classical definition of an infectious disease, the probability of becoming in love with stock must depend on the number of positive contacts. We find that both love and hate emotion behave like infectious diseases. The network allow us to then estimate values for model parameters, and to calculate derived quantities which give insight into the dynamics of emotional contagion.

5.3 Model description and simulation methodology

(a) Basic infectious disease model

In this chapter, we adopt the susceptible-infected susceptible (SIS) model. The SIS model is one of the simplest models in epidemiology and is also known as the contact process model to model emotional cascade and we use network preferential attachment to model herding.

Cascade dynamics has often been described by ordinary differential equations that assume the probability for spreading is uniform (H. W. Hethcote, 2000). However, social networks are not uniformly mixed but are highly heterogeneous and have scale-free properties (K. Ebel, 2002), M. Faloutsos, 1999).

In the simplest infectious disease models (Anderson & May 1991), individuals are classified as occupying one of two states: ‘susceptible’, meaning they do not have the disease, and ‘infected’, meaning they do have the disease.

The disease can be transmitted to a susceptible person when they come into contact with an infected person. The rate of this disease transmission from infected to susceptible is defined as μ, the *transmission probability rate*.

In one class of disease models (susceptible–infected–recovered (SIR)), recovered individuals become immune to further infection and enter a ‘recovered’ state. However, an emotion can occur many times over an individual's life, and therefore it assume infected individuals return to the susceptible state after recovering.

This form of susceptible–infected–susceptible (SIS) model is used to model infectious diseases that do not confer immunity, such as many sexually transmitted diseases.
In the standard SIS model, infection can only be transmitted by having a contact between an infected and a susceptible individual. Emotional ‘infections’, however, can also arise owing to spontaneous factors other than transmission. A diagrammatic representation of the standard SIS model is shown in figure 5.1 and the corresponding differential equations for a well-mixed population are described in equation (5.1).

When the population is not well-mixed but instead constrained on a social network, the transmission rate for each individual depends on the number of infected contacts (n_I) instead of the total number of infected individuals (I).

$$\begin{cases} \dfrac{dS}{dt} = -\mu SI + gI - \phi S \\ \dfrac{dI}{dt} = \mu SI + gI \ + \ \phi S \\ \\ \quad and \quad I + S = N \end{cases} \qquad \text{Equation } (5.1)$$

Where *S* is the number of susceptible individuals, *I* the number of infected individuals μ the transmission rate, *g* the recovery rate, and ϕ the rate of spontaneous infection. This model assumes a constant population size, neglecting birth and death.

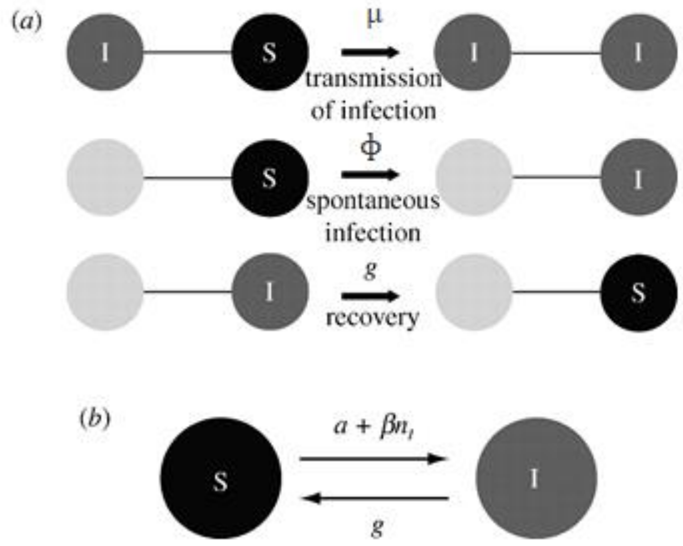


Figure 5.1
The SIS model of infection

We extend the SIS model by adding a term whereby uninfected individuals spontaneously (or 'automatically') become infected at a Variable random rate *a*, independent of infected contacts,We also introduced profit /loss induced emotion which is also independent of network contact but relay purely on price path.

The classical definition of an infectious disease in the susceptible-infected susceptible (SIS) model context is that (i) the probability of an individual transitioning from susceptible to infected is an increasing function of the number of infected contacts, while (ii) the probability of a transition from infected to susceptible (i.e. recovery) is independent of the number or state of contacts. Exposure to infected individuals makes you more likely to become sick, but once you are infected you recover at a constant rate regardless of contacts. In our model we didn't inforce recovery rate so the investors who are in infected-in love with stock – keep in love until the network dynamic and price path cause them to deflect. Also unlike to standard susceptible-infected susceptible (SIS) model were state is split between a binary infected and susceptible our model the state is split along the spectrum from 1 completely in positive to -1 completely negative

-1	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Negative Emotions Neutral Emotions Positive Emotions

This may also allow for more complex and perhaps realistic models, such as modelling emotions as continuous variables rather than discrete states, with transmission depending on the severity of infection.

(b) Model description

We created a network of emotional, semi-rational, and rational investors where the emotions of individual nodes are affected by the performance of the investment, as well as the emotion of the neighbouring investors. The latter is the mechanism through which we define emotional cascades. We adopt the susceptible-infected susceptible (SIS) model, which is one of the simplest models in epidemiology and is also known as the contact process model to model emotional.

In our network the three groups of investors had different characteristics. For the rational investors, we assigned zero emotionality -i.e. that emotion does not play any role in their trading. The other two groups – emotional investors and semi-emotional investors – were assigned emotionality from random from Unif (-1,1) distribution (see Figure 5.2).

The emotional investor buying and selling is purely based on his/her emotions toward the stock i.e. if it is positive they will buy, if it is negative they will short sell, while the rational investor buys the stock if its value is under a perceived fundamental value and short sell the stock if it is above a perceived fundamental value. The semi-emotional investor trading rule is a combination of the two (see Figure 5.3).

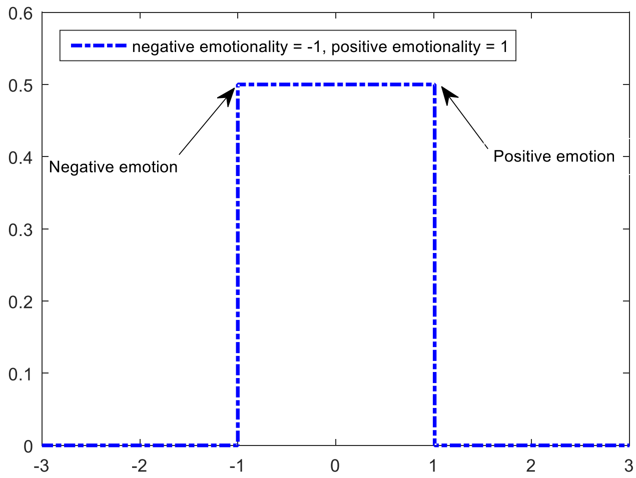


Figure 5.2 The distribution of emotion assigned to the semi-emotional investors and fully emotional investors. Where 1 represents positive/love and -1 represents negative/hate. Zero was the value assigned for the rational investors.

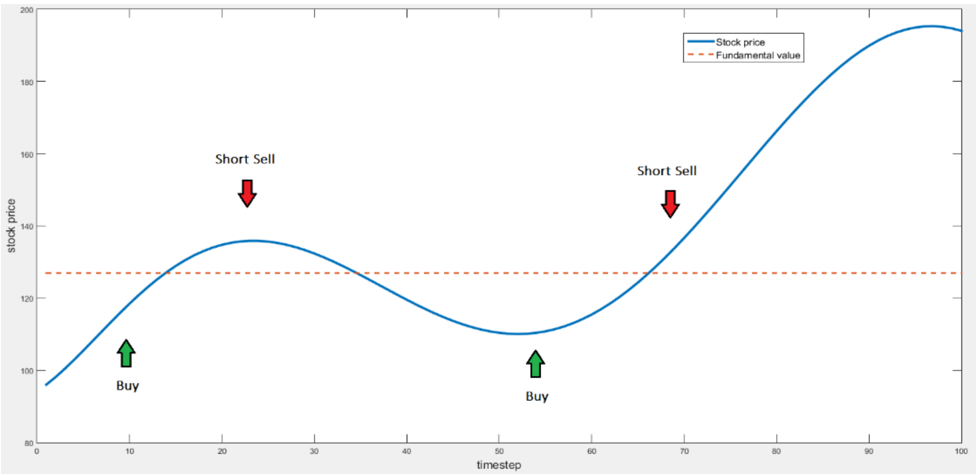
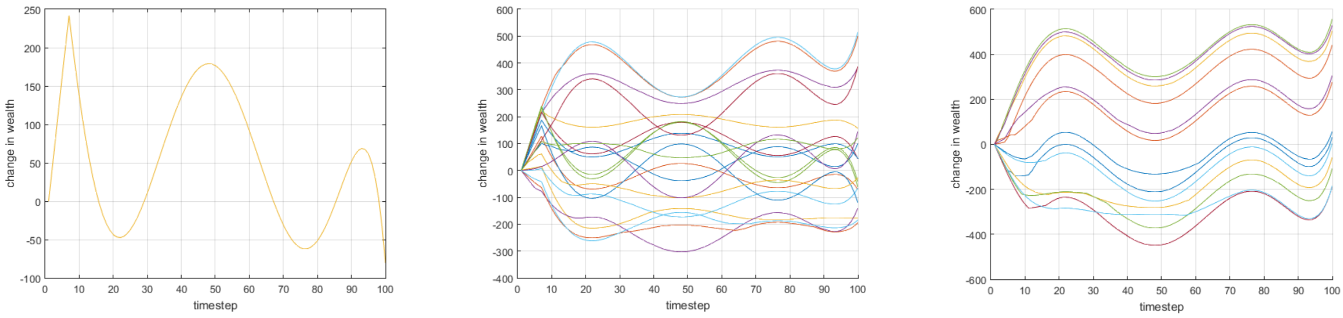


Figure 5.3 The rational investor trading rule for the uptrend price path. Were the fundamental value was assigned as a 0.65*(peak value) to ensure that there will be a period where the stock price is above and below the fundamental value.



rational Investors semi-emotional Investors emotional Investors

Figure 5.4 The wealth change for the three groups of investors for the price path at Figure 5.3

(C) Emotional cascade **Parameter estimation**

Two mechanisms of emotional cascade were introduced: first driven by stock prices, and second by a network-induced emotional cascade.

In the first stages of the process, we assigned randomly love and hate emotion towards the stock. In the latter stages, reality sets in and investors question their decisions and euphoric craze towards the stocks if the stock price moves against their initial beliefs. Taffler and Tuckett (2005) theorise that emotional investors let a range of unconscious and infantile emotions dictate their actions regarding dot.com stocks, rather than knowledge of company fundamental or future growth potential.

For the network emotional cascade, we implemented the susceptible-infected-susceptible (SIS) model. The SIS model is one of the simplest models in epidemiology and is also known as the contact process model (see Figure 5.5).

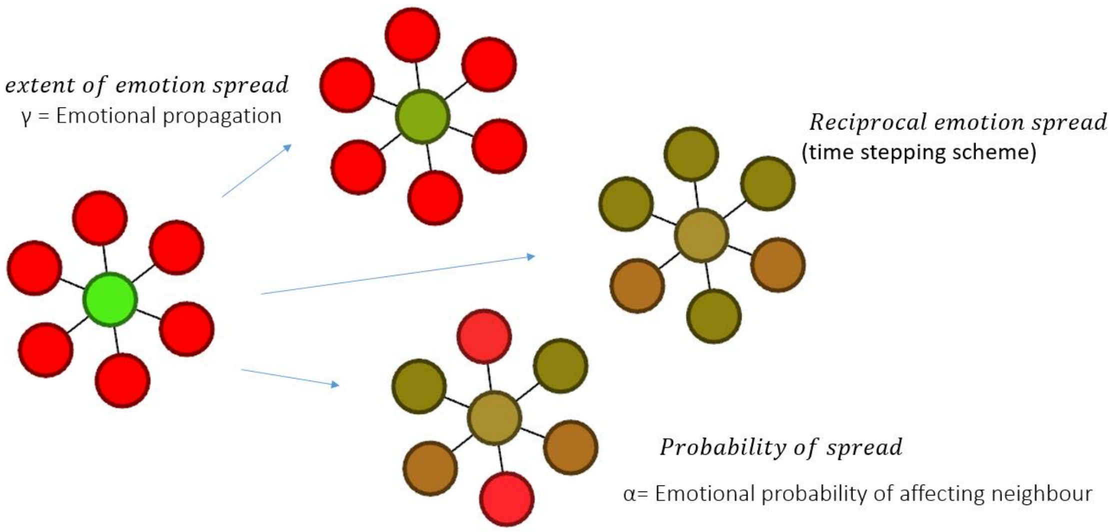


Figure 5.5 Network-induced emotional cascade.

In our model, a population with N investors is categorised into two emotional compartments: Positive (P) and Negative (N). The emotion is transmitted only when a susceptible Investors is in contact with an anther investor.

In the case of a fully mixed population, the model is represented by two stochastic events:

- Stock price level change-induced emotional cascade

$$Em(t+1)_{Trend} = Em(t) + \beta * \frac{P(t)-Ma(x)}{Ma(x)} \qquad \text{Equation (5.2)}$$

- Network induced emotional Cascade

$$Em(t+1)_{Network} = (Em(t+1)_{Trend} + Em(t) * \gamma * Ne(i) \mid \alpha > \text{rand unif}(0,1)) \quad \text{Equation (5.3)}$$

Where

β = Emotional price history factor, bounded between 0 and 1

α= Emotional probability of affecting neighbour, bounded between 0 and 1

γ = Emotional propagation, bounded between 0 and 1

$\mathrm{Ma(x)}$ = x period Stock price moving average

$\mathrm{P(t)}$= price of stock at time (t)

$\mathrm{Em(t)}$ = Investor emotion at time (t)

$\mathrm{Ne(i)}$ = network neighbours (i) emotions

$fv(t)$ = Fundamental Value at time (t)

$Em(t)$=Emotional value of the market participants at time (t) , bounded between 1 and -1

Thus, the change in wealth of each individual investors is given by the Equation (4)

$$Change\ in\ wealth\ = -\left(sgn^{9}\left(fv(t) - P(t)\right) * (1 - \boldsymbol{emotionality}) * 10 + Em(t) * \boldsymbol{emotionality} * 10\right) * \ P(t) \qquad \text{Equation (5.4)}$$

Where **emotionality** in Equation (5.4) is equal to

Rational Investors = zero

Emotional Investors = 1

Semi-emotional Investors = random uniform distribution (0,1)

In Equation (5.4) we see that for the case of the rational investor the change in wealth is a function of only the price change and his/her perceived fundamental value. But for the case of the emotional investor it is their emotion at time (t), while it is the combination of the two for the semi-emotional investor.

[9] In mathematics, the sign function function of a real number x is defined as follows:

$$\mathrm{sgn}(x) := \begin{cases} -1 & \text{if } x < 0, \\ 0 & \text{if } x = 0, \\ 1 & \text{if } x > 0. \end{cases}$$

(D) Network herding

We include a network preferential attachment to model herding, from Barabási, A.-L.; R. Albert (1999), see Figure 5.6.

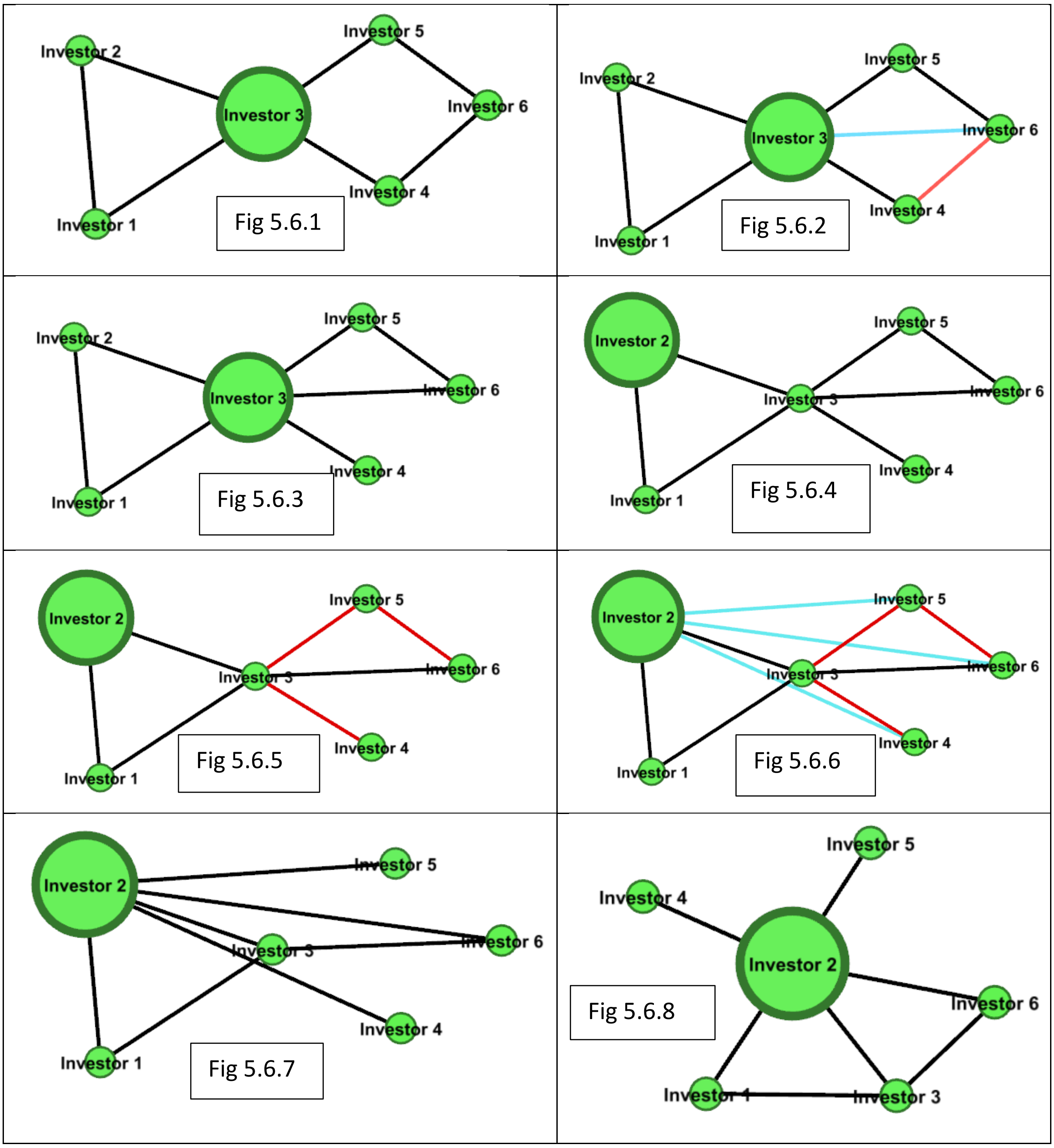


Figure 5.6 Wealth preferential attachment network herding model Barabási, A.-L.; R. Albert (1999).

Most preferential attachment models like those seen in Figure 5.6 seek to rewire to 'rich' nodes. For example, in Fig 5.6.1 Investor 3 is the 'rich' node. Then in Fig 5.6.2 Investor 6 breaks its tie with Investor 4 and reattaches to Investor 3. The resulting network would look like Fig 5.6.3.

This concept tries to mimic the concept of 'fitness' in growing networks. It is not perfect but can produce a power-law distribution. We propose a fitness measure that is not based on its topology, understanding that topology can change drastically on performance within the market. In Fig 5.6.4 Investor 2 becomes the best performing node. The network reattach itself to a highly performing Investor (Fig 5.6.5, Fig 5.6.6), making the performing investor more central (Fig 5.6.7, Fig 5.6.8).

In our model, a network is created that most accurately describes a real network. The nodes represent investors, and the edges (the links) represent some social relationship between them.

1. The performance of each of the investors is simulated.
2. The probability of rewiring a given connection is a flat p_{rewire} for all edges (once).
3. An edge will be rewired to a given node with the probability: $p_i = \frac{Wealth_i}{\sum_N Wealth_j}$
4. If no suitable node is found, no rewiring occurs.

$$\frac{\partial k_i}{\partial t} = k_i(t+1) - k_i(t) = \sum_N qk_j(t) \frac{Wealth_i(t)}{\sum_N Wealth_j(t)} - qk_i(t)$$

$$k_i(t+1) = k_i(t) + \sum_N qk_j(t) \frac{Wealth_i(t)}{\sum_N Wealth_j(t)} - qk_i(t)$$

$$\frac{k_i(t+1)}{k_i(t)} = 1 + q \cdot \frac{\sum_N k_j(t)}{k_i(t)} \cdot \frac{Wealth_i(t)}{\sum_N Wealth_j(t)} - q$$

If:

$$\frac{Number\ of\ edges}{k_i(t)} \cdot \frac{Wealth_i(t)}{\sum_N Wealth_j(t)} > 1$$

The number of nodes will increase for node *i*.

Overall dynamics of the topology will depend on the performance of the nodes and the proportion of edges a node has (see Figure 5.7).

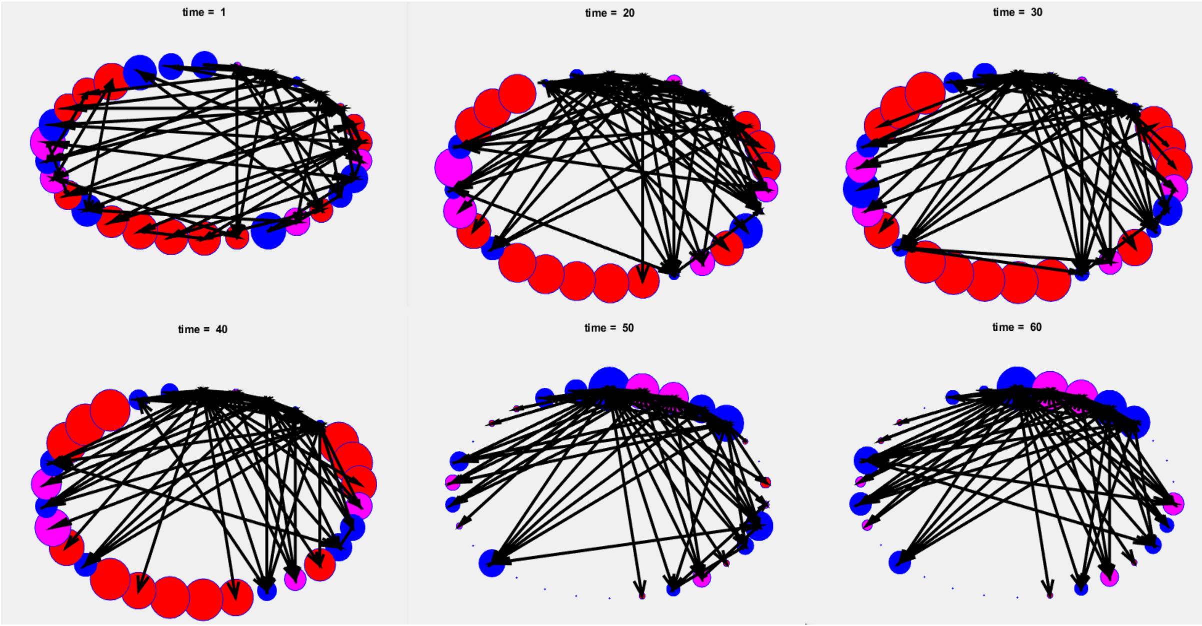


Figure 5.7. Network Herding Visualisation where nodes represent market participants and arrows represent participants' links (Full MATLAB code implementation is in Appendix 2).

5.4 Results

A network of investors were given four exogenous price paths as see in Figure 5.8 , where investors' wealth changed over each time step according to Equation 3. Investor's emotionality was observed and visualised –see appendix 1 -using different network setting. The model parameters are shown in table 5.1.

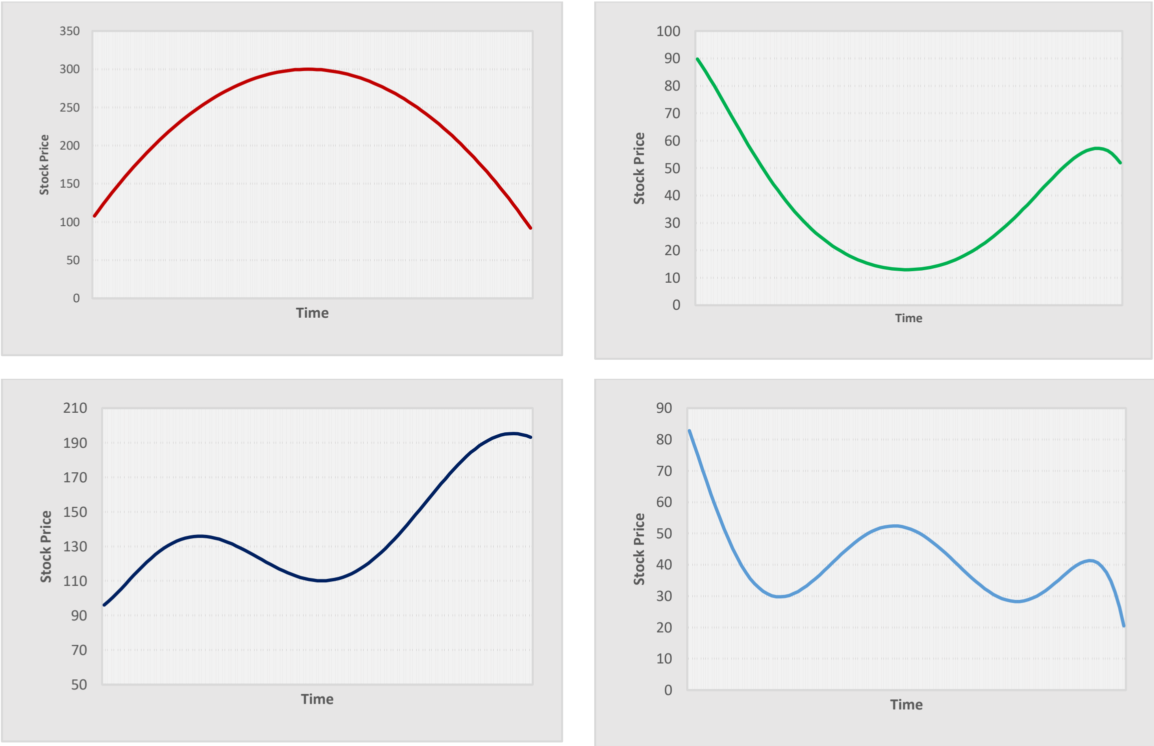


Figure 5.8. Four price patterns: n-shaped, u-shaped, uptrend and downtrend.

N =Size of network (N)
m_0 =Minimum number of connections
$n(t)$ = Number of time steps
β = Emotional price history factor
α= Emotional probability of affecting the neighbour
γ = Emotional propagation
$Ma(x)$ = x period moving average
$P(t)$ = price of stock at time (t)
$Em(t)$ = Investor emotion at time (t)
$Ne(i)$ = network neighbours (i) emotions
$pRI(\%)$ = Percentage of rational Investors
$pEI(\%)$ = Percentage of emotional Investors
$pSE(\%)$ = Percentage of semi-emotional Investors P =Probability of rewiring

Table 5.1 Model input parameters

The simulation was conducted and investors' emotions were observed over 100-time steps. We also conducted a network parameter sweep and observed emotionality cascade sensitivity as we altered the value of the parameters. Three parameters were of interest:

1- **Time to full cascade,** which is the number of time steps it takes for the all the network participants emotionality to converge to Positive (1) or Negative (-1). See Figure 5.9.

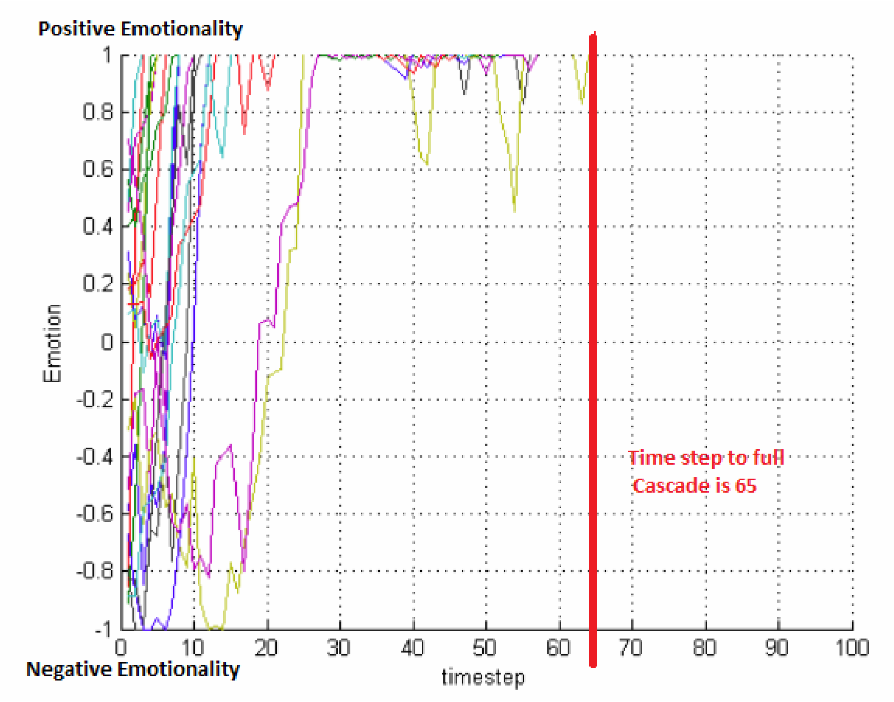


Figure 5.9 shows all investor participants emotionality converge to positive emotion at timestep 65. Notice that the emotionality of investors was randomly allocated between negative and positive emotion at time zero, and emotional cascade occurs due to network interaction and change in the price path.

2- **The density of the cascade** refers to a measure of the strength and variability of the cascade. The closer emotionality of the investors to each other the stronger the cascade density (see Figure 5.10 and 5.11).

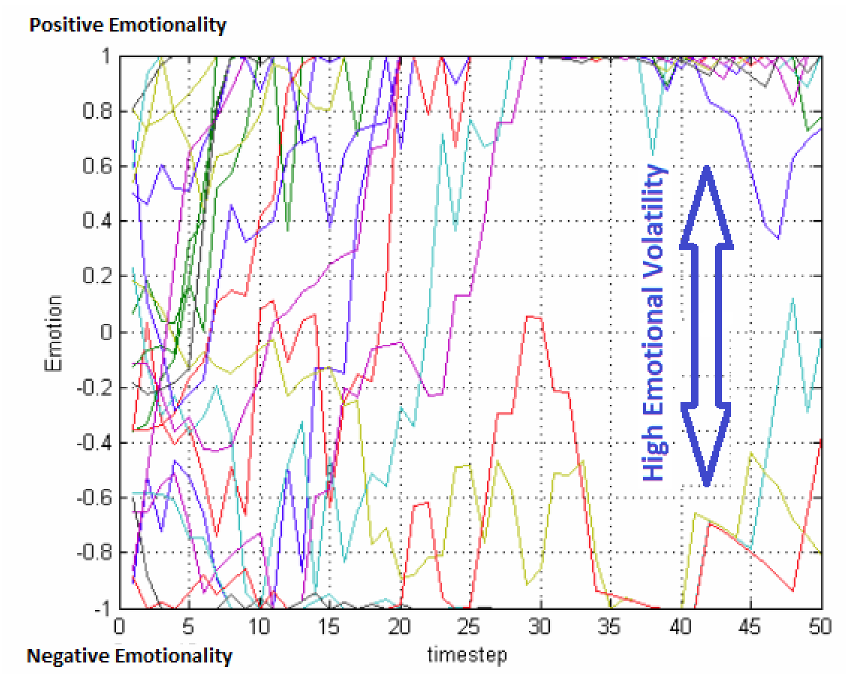


Figure 5.10 shows all investor participants' emotionality changes at each time step. Full cascade never occurs in this price path and the emotionality of the investors had high volatility.

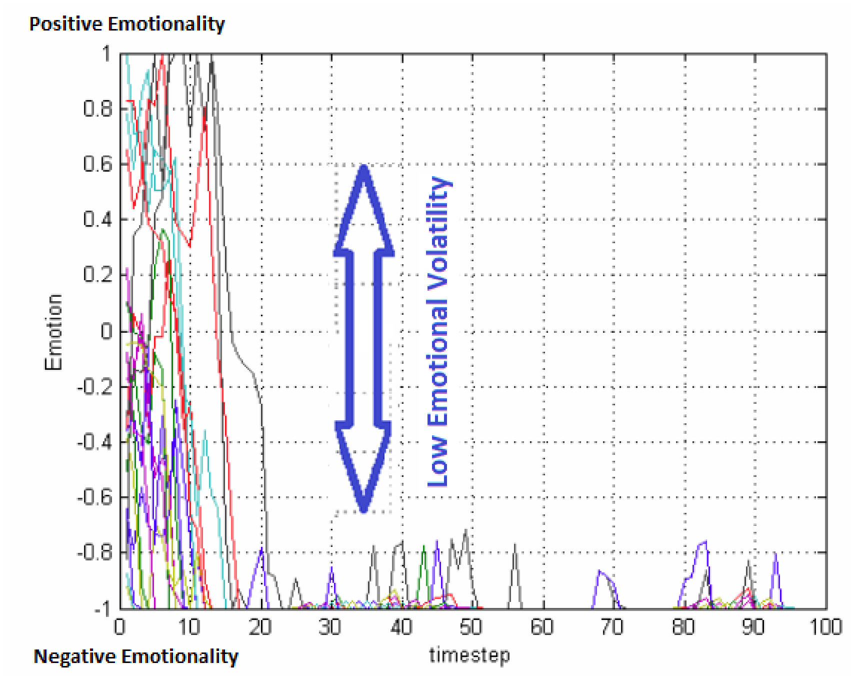


Figure 5.11 shows all investor participants' emotionality for the same price path above, but as we change the network parameters the volatility of the emotionality is much less than before, and full cascade occurs.

3- **Cascade parameter value** refers to the smallest value of network parameter when full cascade is observed. See Figure 5.12 and 5.13.

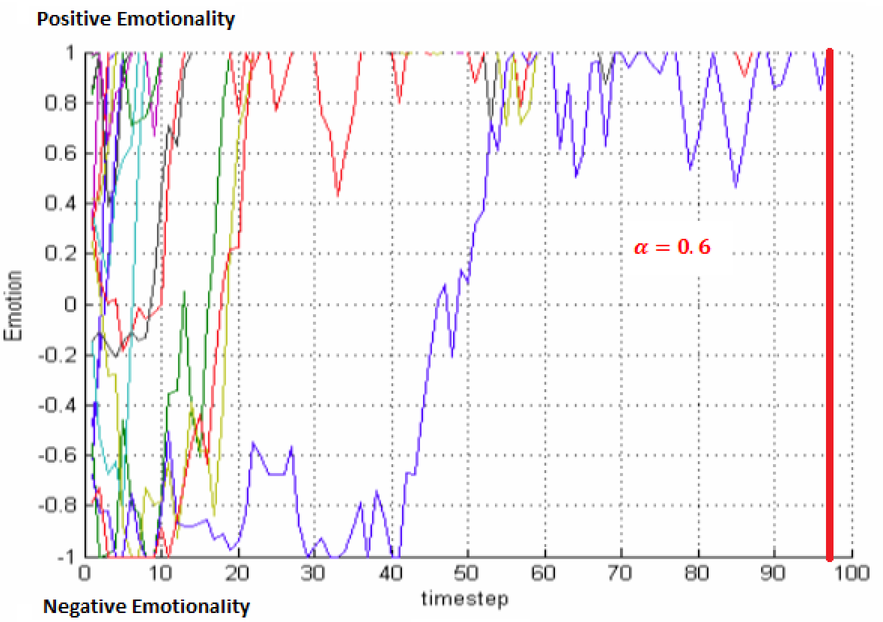


Figure 5.12 shows all investor participants' emotionality changes at each timestep. Full cascade occurs at time step 95. For this run, the network parameters alpha is 0.6, beta and gamma were 0.35, for 50 participants and the minimum number of connections was set to 3.

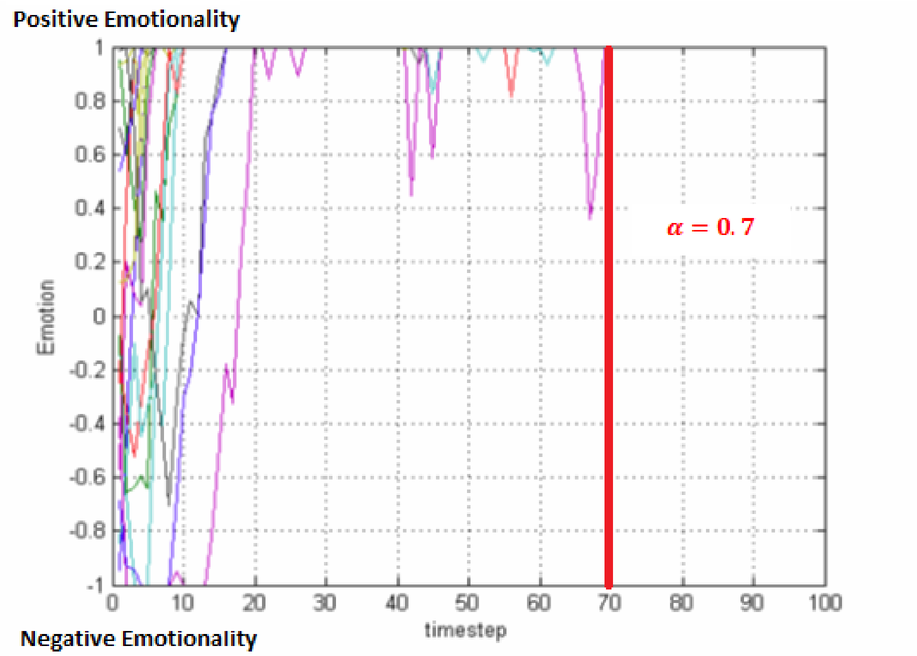


Figure 5.13 shows all investor participants' emotionality changes at each timestep. Full cascade occurs at time step 70. For this run the network parameters alpha is 0.7, and all the other network structure and parameters were the same as in Figure 5.12.

The results of the network parameter sweep are presented in Tables 5.2-4.

Cascade Emotion parameters	**Trend Path**	**Cascade parameter value**	**Time step to full cascade**	**The density of cascade (ranked 1-12) where 12 is the highest density.**
Alpha (Emotional probability of affecting neighbour)	n-shape (Fig 1, Appendix 1)	0.3 $(\beta, \gamma = 0.35)$	30	8
	U-shape (Fig 3, Appendix 1)	0.4 $(\beta, \gamma = 0.35)$	40	2
	Upward (Fig 5, Appendix 1)	0.7 $(\beta, \gamma = 0.35)$	30	10
	Downward (Fig 7, Appendix 1)	0.3 $(\beta, \gamma = 0.35)$	30	9
Beta (Emotional price history factor)	n-shape (Fig 9, Appendix 1)	0.3 $(\alpha, \gamma = 0.35)$	60	2
	U-shape (Fig 10, Appendix 1)	0.2 $(\alpha, \gamma = 0.35)$	50	5
	Upward (Fig 11, Appendix 1)	0.7 $(\alpha, \gamma = 0.35)$	80	3
	Downward (Fig 12, Appendix 1)	0.3 $(\alpha, \gamma = 0.35)$	30	6
Gamma (Emotional propagation)	n-shape (Fig 13, Appendix 1)	0.2 $(\alpha, \beta = 0.35)$	30	12
	U-shape (Fig 14, Appendix 1)	0.01 $(\alpha, \beta = 0.35)$	30	11
	Upward (Fig 15, Appendix 1)	0.5 $(\alpha, \beta = 0.35)$	80	4
	Downward (Fig 16, Appendix 1)	0.3 $(\alpha, \beta = 0.35)$	70	7

Table 5.2. Simulations were conducted and emotion was observed over 100 timesteps. During the simulation we fixed all the network structure parameters i.e. network size to 50, and a minimum number of connections to 3, using equal split between fundamental rational trader, emotional and semi-emotional trader i.e. 1/3.

Observations from the table 5.2 include that as we alter the network emotional parameters (alpha, beta, gamma), the price trend path plays a big role in determining the strength of the emotional cascade. We also notice for the upward trending and down trending paths that the strength of the cascade is stronger than for the U and n-shaped paths. Furthermore, we see that gamma – Investors

Emotional propagation – plays an important role in density cascade, and the network reaches a full cascade at a faster rate than alpha and beta.

Network Structure	**Trend Path**	**Cascade parameter value**	**Time step to full cascade**	**The density of cascade** **(ranked 1-8) where 8 is the highest Density.**
Size of network	n-shape (Fig 23, Appendix 1)	10 ($m_o = 3$)	10	8
	U-shape (Fig 24, Appendix 1)	10 ($m_o = 3$)	20	7
	Upward (Fig 25, Appendix 1)	20 ($m_o = 3$)	15	5
	Downward (Fig 26, Appendix 1)	10 ($m_o = 3$)	20	6
Minimum number of connections	n-shape (Fig 18, Appendix 1)	3 ($N = 100$)	30	1
	U-shape (Fig 19, Appendix 1)	3 ($N = 100$)	20	3
	Upward (Fig 20, Appendix 1)	3 ($N = 100$)	40	2
	Downward (Fig 21, Appendix 1)	2 ($N = 100$)	70	4

Table 5.3. Simulations were conducted and emotion was observed over 100timesteps. During the simulation we fixed all the cascade emotion parameters (α, β, γ) to 0.35, again using equal split between fundamental rational trader, emotional and semi-emotional trader i.e. 1/3.

Observations from results in Table 5.3 above include that as we altered the network size from 10-20-50-100 and the network minimum connection from 1-2-3-4, we noticed that the size of the network played a more important role in the cascade than the number of connections, i.e. the network reaches full cascade at faster timesteps and the density is higher. The price path also plays an important role in the cascade density. For the upward and downward price path, the minimum number of connections was the dominate variable but for the U and n-shape it was the size of the network. In addition, the time to full cascade was reached faster for the U and n-shapes in both cases.

Network Property	Trend Path	Cascade parameter value	Time step to full cascade	The density of cascade (ranked 1-12) where 12 is the highest Density.
Percentage of rational Investors	n-shape (Fig 35, Appendix 1)	50%-the rest is emotional	75	2
	U-shape (Fig 36, Appendix 1)	50%%-the rest is emotional	45	4
	Upward (Fig 37, Appendix 1)	50%%-the rest is emotional	30	1
	Downward (Fig 38, Appendix 1)	50%%-the rest is emotional	25	4
Percentage of emotional Investors	n-shape (Fig 27, Appendix 1)	100%	10	12
	U-shape (Fig 28, Appendix 1)	100%	15	10
	Upward (Fig 29, Appendix 1)	100%	15	9
	Downward (Fig 30, Appendix 1)	100%	20	11
Percentage of semi-emotional Investors	n-shape (Fig 31, Appendix 1)	50%%-the rest is emotional	No full cascade	5
	U-shape (Fig 32, Appendix 1)	50%%-the rest is emotional	25	6
	Upward (Fig 33, Appendix 1)	50%%-the rest is emotional	20	7
	Downward (Fig 34, Appendix 1)	50%%-the rest is emotional	40	8

Table 5.4. Simulations were conducted and emotion was observed over 100 timesteps. During the simulation we fixed all the cascade emotion parameters (α, β, γ) to 0.35. We also fixed all the network structure parameters i.e. network size to 50, and minimum number of connections to 3.

In Table 5.4 above, we looked at how altering the percentage of rational to semi-emotional to fully emotional investors in the network impacts the emotional cascade. As the percentage of emotional investees increases in the network, the stronger the emotional cascade, followed by the semi-emotional. Moreover, the price path didn't play a significant role in the strength of the emotional cascade as the percentage of emotional investors increased or decreased.

5.5 Discussion

We have developed a network emotional cascade and herding model using scale-free networks and showed how the cascade and herding developed and evolved over four price paths. In our model, three independent parameters dictate the emotional cascade (alpha, beta, gamma), and these three parameters contribute positively and increase the likelihood of the emotional cascade to occur because as these parameters increase in value the density of the cascade increases – i.e. reducing the variance of emotion cascade.

Our simulation concluded that as the percentage number of the market participants classified as emotional increases in value, this increases the likelihood of emotional cascade. In contrast, as the number of the market participants decreases -i.e. the N size of the network decreases, this also has positive inducing effect on the emotional cascade. And regarding the minimum number of connections, the more connections the higher the likelihood that emotional cascade will occur.

Regarding trading performance/wealth, the result was a mixed. For the declining trend and the upward trend, emotional investors outperformed the other two groups (rational and semi-emotional investors), but the story is the opposite for the U and n-shape trends. This is inline with our expectation, because as the market is trending emotional investors will herd toward buying or selling stock, and profit is generated due to the continuity of the trend .

Figure 5.14 shows a system diagram of the interaction of all the elements of our model. Note Emotional cascade and Herding interaction within one system.

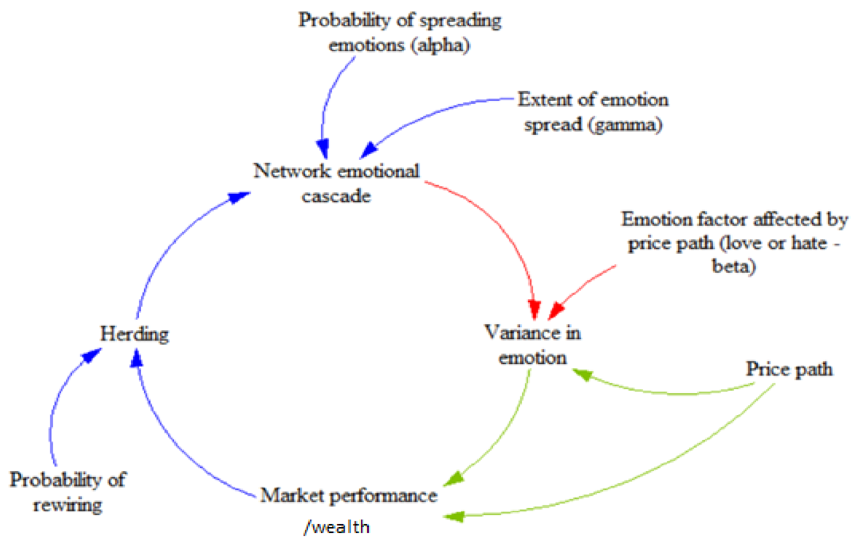


Figure 5.14 System dynamic model diagram of emotional and herding cascade. Blue lines show positive feedback, red lines negative feedback, green is neutral.

This infectious disease methodology has numerous advantages over techniques that examine correlations in behaviours of connected individuals. Our technique controls for selection bias in choosing contacts with similar behaviour, as well as confounding environmental factors synchronously affecting contacts.

Much of the appeal of our approach is the significance of our results despite the great simplicity of the model used, and the assumptions made about the investors. Determining the various transition rates for the model requires the implicit assumption that all individuals are identical in their susceptibility to various emotional states. These rates therefore represent ensemble averages over the population. In reality, individuals are likely to differ in their predispositions to various emotional states.

5.6 Conclusions and further work

We have introduced a novel framework for formalizing social contagion derived from the study of infectious diseases, which can be used to study the spread of emotions or other social phenomena. our simulation show that long-term emotional states can spread between socially connected individuals. and that rates of becoming 'in love' or 'hate' increase with the number of 'infected' contacts (i.e. are contagious) .it assumes that the probability of becoming in love with stock is independent of an individual's history of emotional episodes and mood.

Our results give insight into the transmissive nature of positive and negative emotions, and our model provides a theoretical framework for studying the spread of other emotions, as well as a wide range of other social phenomena. Determining to what extent particular emotions or behaviours are infectious is a promising direction for further research with important implications for social science, epidemiology and economic policy.

We also could be calibrated on financial market data to try to replicate the stylized facts of financial markets, such as volatility clustering and fat tails in the distribution of returns. This can be done by applying method of simulated moments (MSM), a generic method for estimating parameters in statistical models-. In addition, introducing exogenous time series to the model in order to replicate real market trading scenarios. Finally, different model parameters could be investigated, such as for trust, confidence, reliability, performance. These could, for example, take the recent performance of agents into account during herding/emotional cascade mechanisms.

Chapter 6 Conclusions

6.1 Emotions and decision making

This thesis has highlighted the dichotomous role of emotion as both a facilitator and bias to financial decision-making. During our trading game experiments detailed in Chapter 3, autonomic arousal was found to play a cuing role for negative outcome as speculated by the somatic marker hypothesis (SMH). Whilst extreme overt emotions, such as a high positive PANAS score and high risk aversion, may in fact hinder trading performance in bear market situation.

Additionally, this study highlights several important methodological implications to consider. Firstly, the experiments revealed that differentiating arousal and valence when considering overt emotional expression was found to be crucial. Secondly, the study stressed the need for further investigation into how and why the different measures of galvanic skin response (GSR), namely amplitude and frequency, relate differently to financial decision-making.

Our study also had some theoretical implications demonstrating that the financial and psychological theoretical account may not be contradictory, but rather complementary. Indeed, by looking at emotions-as-facilitators versus emotions-as-bias-inducers, we have demonstrated that these may in fact be complementary. Autonomic arousal may facilitate decision-making by cuing salient trials through the fast implicit ‘system one’ process. But the actual experience of emotions and resulting behaviour may, if too extreme, hinder performance in trading situations. As such, system one may cue for potential negative outcomes, but the actual integration of this information and the subsequent functional or dysfunctional behaviour may be related to the slower, more conscious system two processing whereby extreme emotions translate into dysfunctional behaviour.

As we have found high risk aversion to be particularly adverse in the context of a bear market, we suggest it may be useful to assess an investor’s risk profile and advise particularly high risk averse individuals to investments choices with the least bear market trends.

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Overall, our work contributes to the debate over the effect of traders’ emotions on financial market behaviour and performance. We find that an optimal level of risk-aversion may exist that maximises performance, and that extremely high risk-aversion can actually be a burden in a bear market, leading to paralysis, and 'sitting in' losing shares. In terms of the fierce debate as to whether emotions are good or bad for performance, we have contributed to the literature by experimentally demonstrating that there is an optimal level of emotions.

Thus, one major contribution of our analysis is that we employ experimental and neuro-scientific methods to examine the relationship between risk-preferences (CRRA), emotions, and trading behaviour and performance. A second major contribution is that we use our analysis to develop potentially practical tool for IFAs to consider when advising their clients (see next section 3.11 Lessons from risk-profiling). Thus, we develop a risk-measure which we term 'psychological utility' which incorporates traders' emotions.

Finally, our study's sample was relatively mixed with both students and University of Bath employees. It would be very interesting to conduct this study on professional traders. Here, there is no agreement in the literature as to how expertise influences financial decision-making (Edwards & Caglayan, 2001), risk aversion (Menkhoff, Schmidt, & Brozynski, 2006) and emotional biases (Glaser, Langer, & Weber, 2005) among professionals in the field. Ericsson et al. (2005) suggest that financial expertise is developed through deliberate practice, resulting in cognitive adaptation that increases reasoning abilities and reduce biases. However, in the field empirical research has shown that younger, inexperienced fund managers earn significantly higher returns than their older and more experienced colleagues (Chevalier & Ellison, 1999), and that financial experts are prone to psychological biases such as overconfidence (Shefrin, 2000; Baker & Nofsinger, 2002).

6.2 Lessons from risk-profiling

Risk profiling has recently been implemented in financial practise due to the increasing demands on financial advisers to communicate risk efficiently to their client. However, none of these risk-profiling tools have been academically validated and researched. Moreover, these usually comprise of a single financial questionnaire whilst we, as detailed in Chapter 4, have utilised a variety of measures combining different approaches stemming from neuropsychological and financial theories thereby providing a more comprehensive assessment tool in the form of market Risk Profiler.

The 'Stage-Gate 3 Scorecard for Project Selection', as described in Chapter 4, has demonstrated itself to be a useful method of rapidly evaluating the commercial potential of emergent products, such as the CheckRisk system we developed. The Stage-Gate 3 Scorecard is particularly well suited because the organisation can then go on to follow the Stage-Gate process until launch thus ensuring it follows 'best practice' guidelines throughout the commercialisation process.

This is important because financial regulators such as the UK Financial Services Authority have expressed concerns that financial advisers may take the output of a risk profiling tool and apply the results without further deliberation. Our risk-profiling system openly encourages debate between the independent financial adviser (IFA) with the clients about their attitude to risk and what this means in form of asset allocation. The system reports the investor's scores and categorises it into one of seven risk bands, then continues to evaluate how the given answers compare with peers within the group for different views on risk tolerance, including making financial choices and reacting to financial disappointments. This practice enables the IFA to identify anomalies in the answers and induces discussion about their attitude to market risk.

Data from our risk-profiling questionnaire as detailed in Chapter 3 have revealed interesting insights. We have found high risk aversion to be particularly adverse in the context of a bear market. It may be of use to assess an investor's risk profile and advise particularly high risk averse individuals to investment choices with the least bear market trends.

A second contribution of our analysis in Chapter 4 is that it has implications for the IFA industry. Our experiment helps IFAs to understand that emotions can have large effects on investor performance and well-being. Equipped with this knowledge, IFAs can improve their assistance to their existing clients, helping them to plan both financially and emotionally.

In addition, our work could help IFAs in reaching out to potential new clients. Although we do not directly consider an investor's choice whether to involve an IFA or not, our work demonstrates that traders' risk preferences and emotions can have crucial effects on performance in the trading game and investor well-being. Thus, IFAs could use our analysis as a 'marketing tool' to promote themselves and their services to potential clients, particularly for 'marginal clients' that are undecided between involving an IFA or 'going it alone'.

6.3 How emotions, risk-taking, and decisions can cascade through networks

One way to model the effect of investor behaviour and emotions on the market as a whole is using network analysis. In this thesis, in Chapter 5 we described how we developed network emotional cascade and herding model using scale-free networks and showed how cascade and herding develops and evolves over four different price paths. We have found that network structure and participant's emotional characteristics play a big part in shaping the emotional cascade.

In our model, three independent parameters dictated the emotional cascade (Alpha, Beta, Gamma). These three parameters contribute positively and increase the likelihood of the emotional cascade to occur, and as these parameters increase in value the density of the cascade increases, and reduces the variance of the emotional cascade.

Our simulation concluded that as the proportion of the emotional market participants increases in value, this in turn increases the likelihood of an emotional cascade. In addition, as the number of market participants decreases (the N size of the network) -this also has a positive inducing effect on the emotional cascade, and the higher the number of connections the more likely it is that an emotional cascade will occur.

Much of the appeal of our approach is the significance of our results despite the great simplicity of the model used, and the assumptions made about the investors. Determining the various transition rates for the model requires the implicit assumption that all individuals are identical in their susceptibility to various emotional states. These rates therefore represent ensemble averages over the population. In reality, individuals are likely to differ in their predispositions to various emotional states.

Further work in this area could include introducing exogenous time series to the model to replicate real market trading scenarios. This work could also be calibrated on financial market data to attempt to replicate aspects of financial markets such as volatility clustering and fat tails in the distribution of returns. This can be done by applying method of simulated moments (MSM), a generic method for estimating parameters in statistical models-. Finally, to investigate different model parameters, such as trust, confidence, reliability, performance, data on the most recent performance of financial agents could be consider during the herding and emotional cascade mechanisms.

Appendices

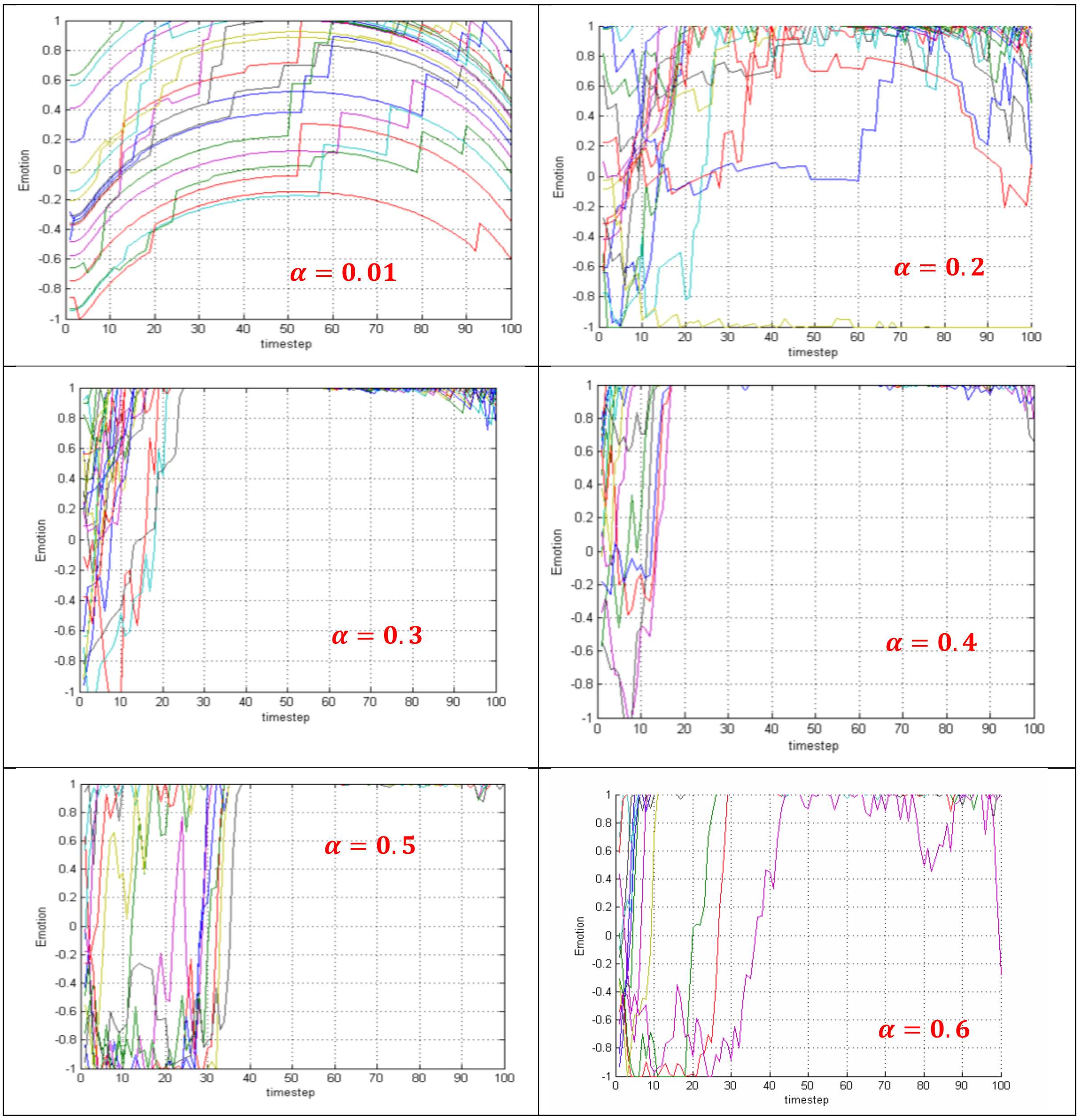
Appendix 1 Emotional Network Visualization

Parameter Testing

α= Emotional probability of affecting the neighbour

β = Emotional price history factor

γ = Emotional propagation



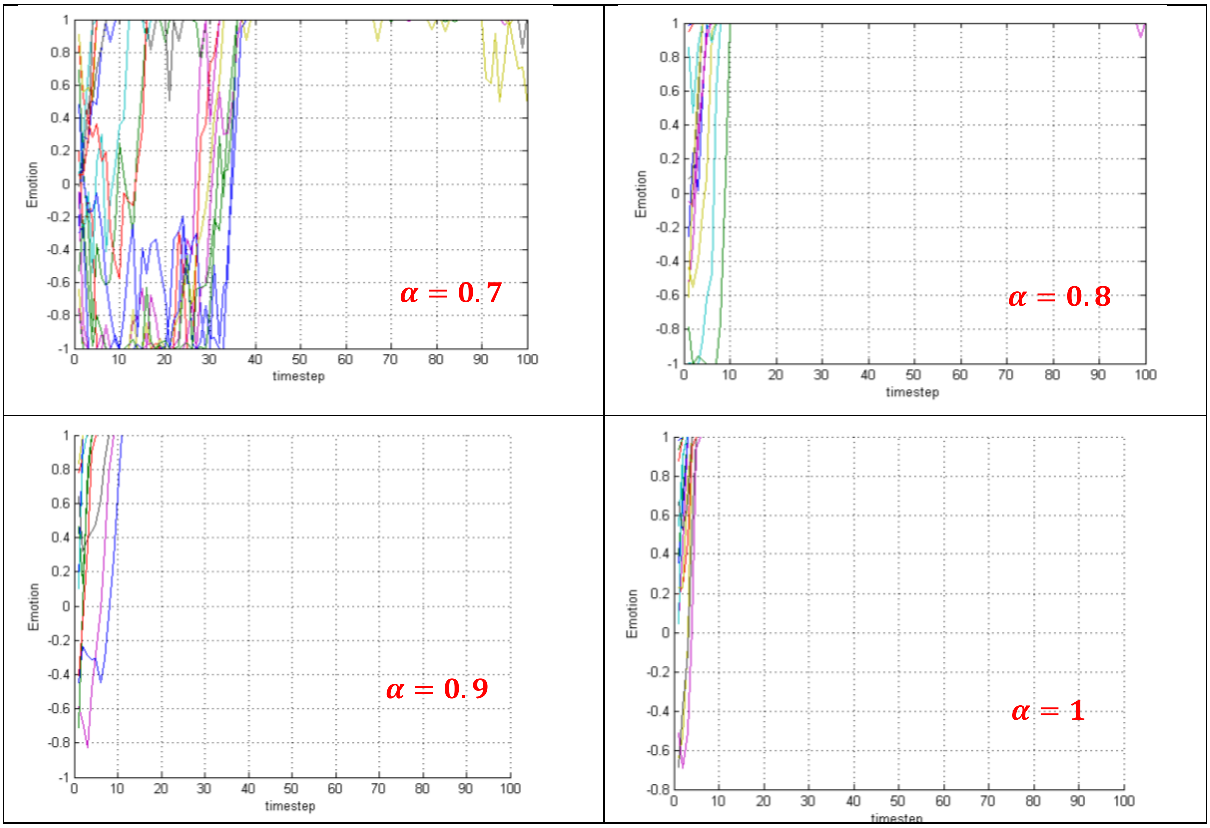


Figure (1) shows emotional-investors emotions changes with α for the n shape price path shown in figure (2) were the other Cascade parameters β and γ were fixed at 0.35 , N=50 and m_0= 3

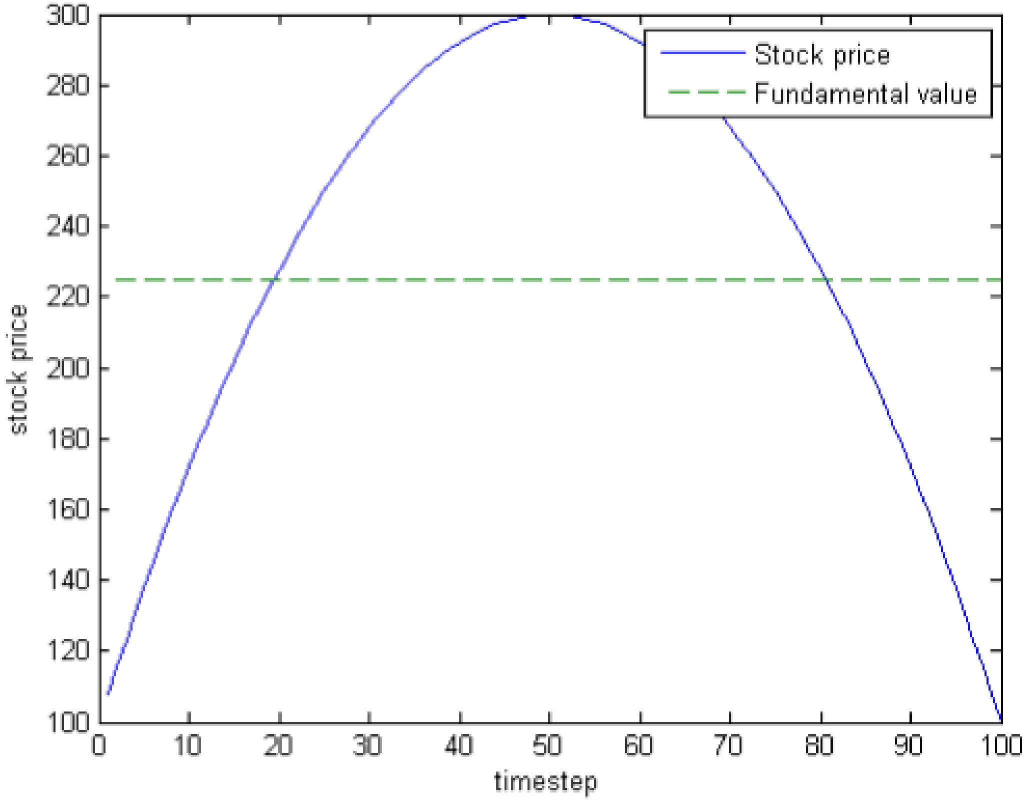
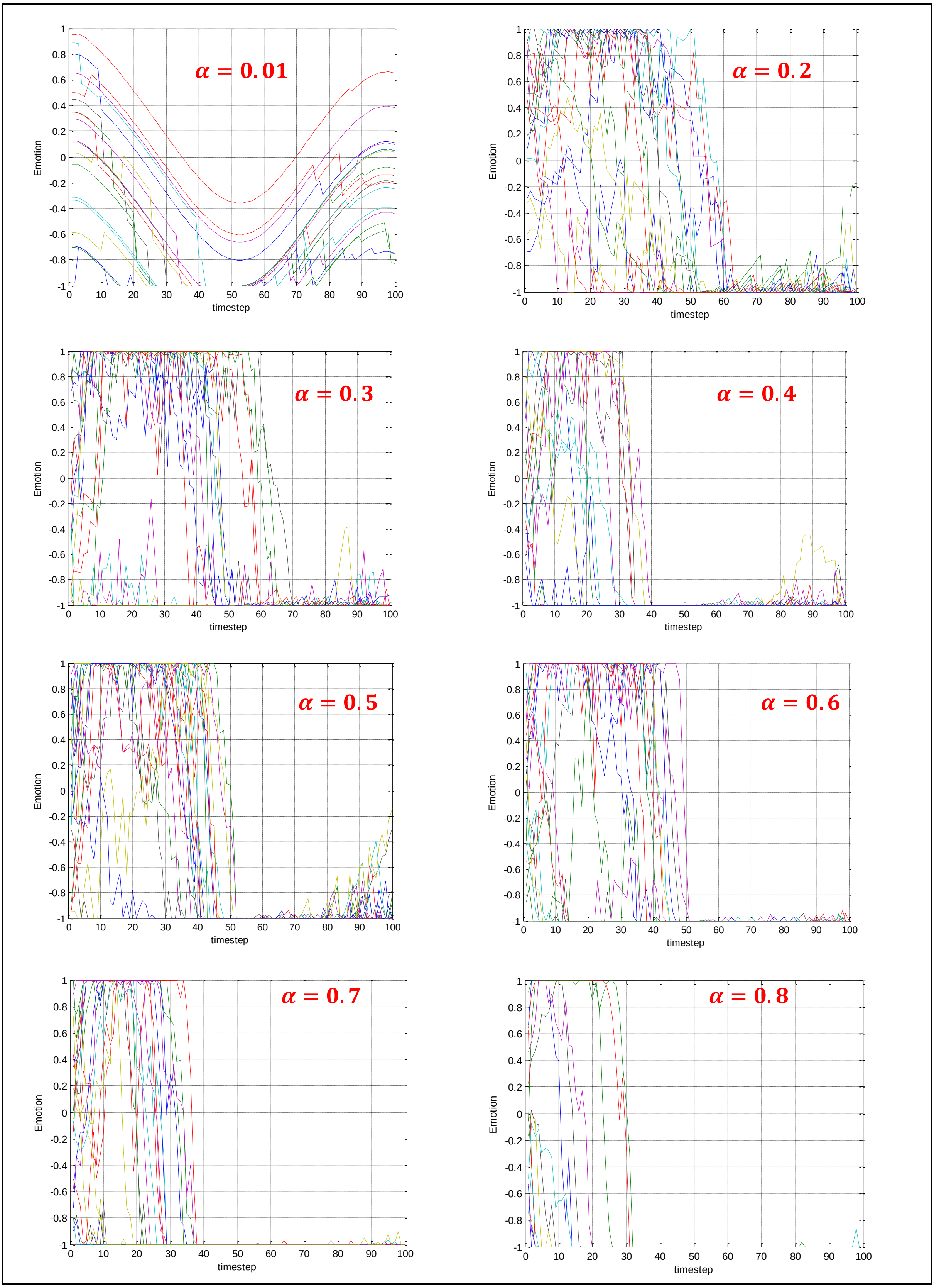


Figure (2) n shape price path and its perceived fundament value at 0.75*peak value


$\alpha = 0.01$
$\alpha = 0.2$
$\alpha = 0.3$
$\alpha = 0.4$
$\alpha = 0.5$
$\alpha = 0.6$
$\alpha = 0.7$
$\alpha = 0.8$
Emotion
timestep

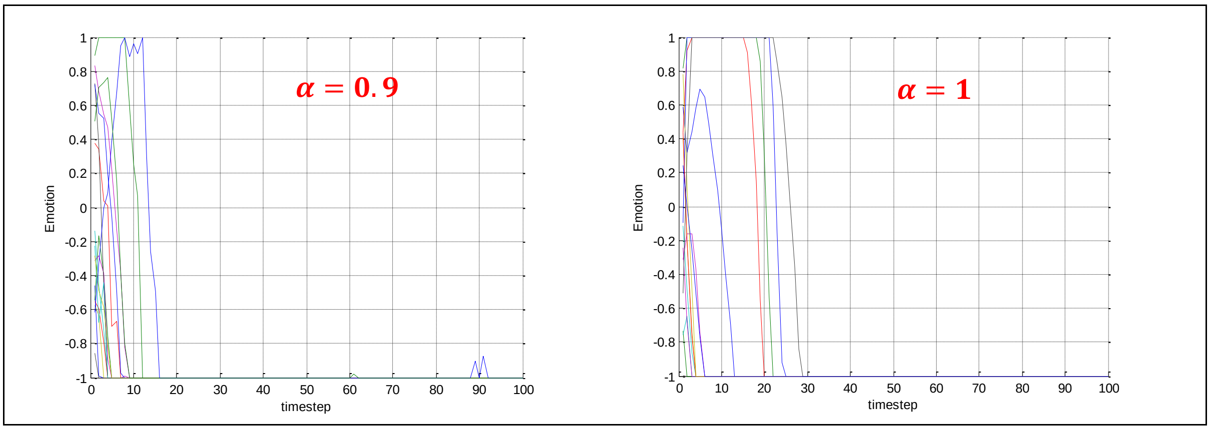


Figure (3) shows emotional-investors emotions changes with α for the U shape price path shown in figure (4) were the other Cascade parameters β and γ were fixed at 0.35 , N=50 and m_0= 3

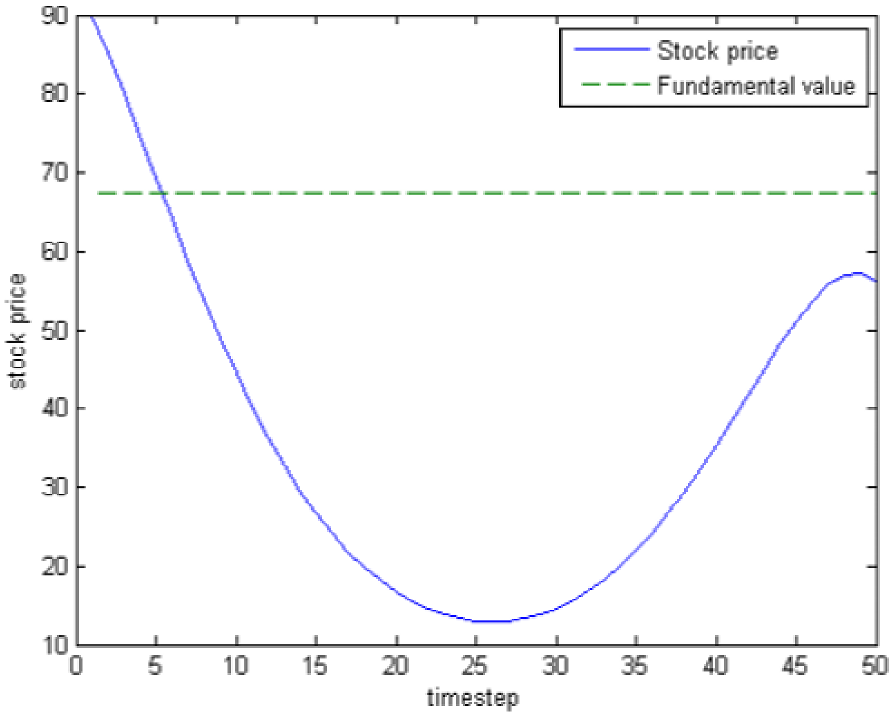
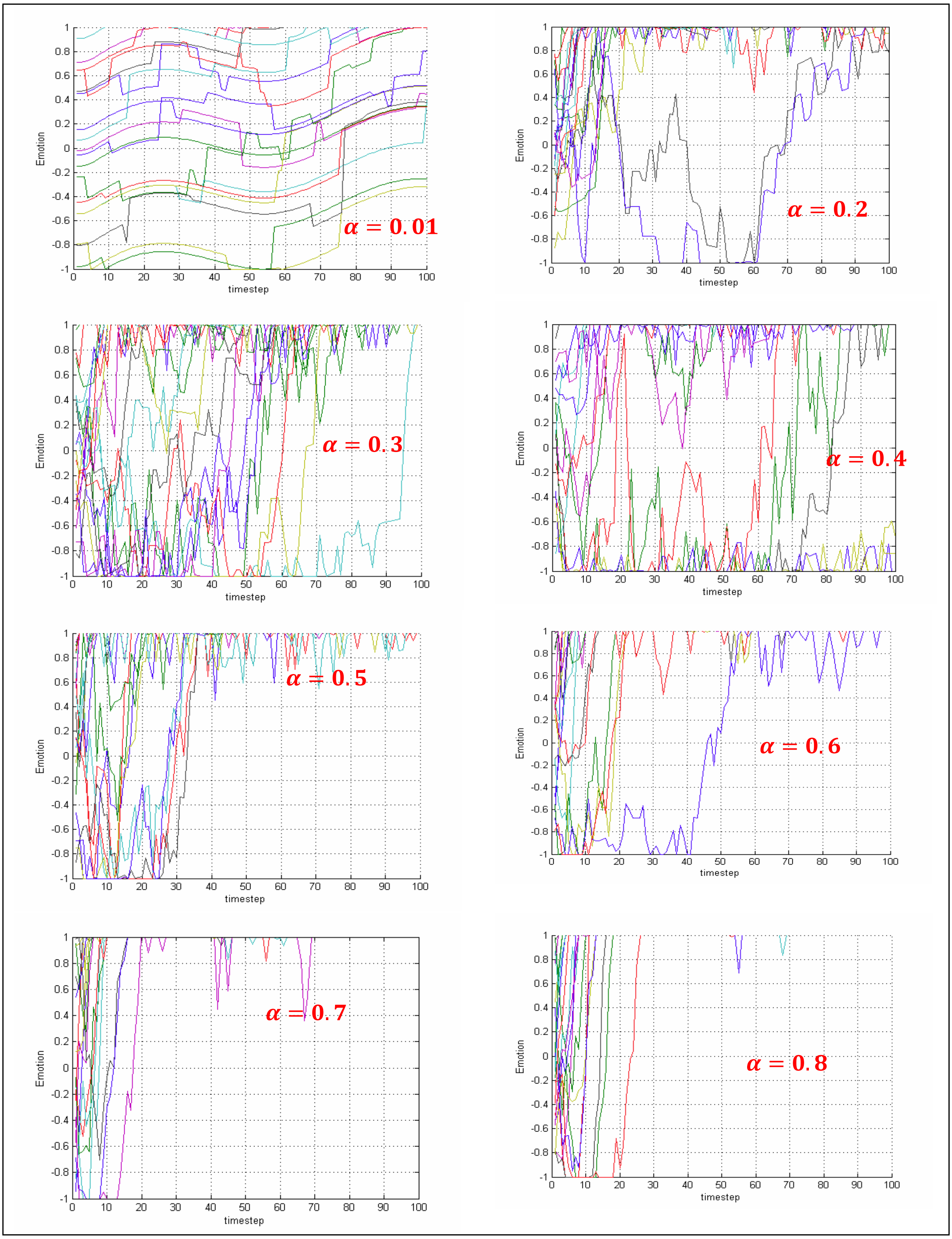


Figure (4) U shape price path and its perceived fundament value at 0.75*peak value


Emotion
timestep
$\alpha = 0.01$
$\alpha = 0.2$
$\alpha = 0.3$
$\alpha = 0.4$
$\alpha = 0.5$
$\alpha = 0.6$
$\alpha = 0.7$
$\alpha = 0.8$

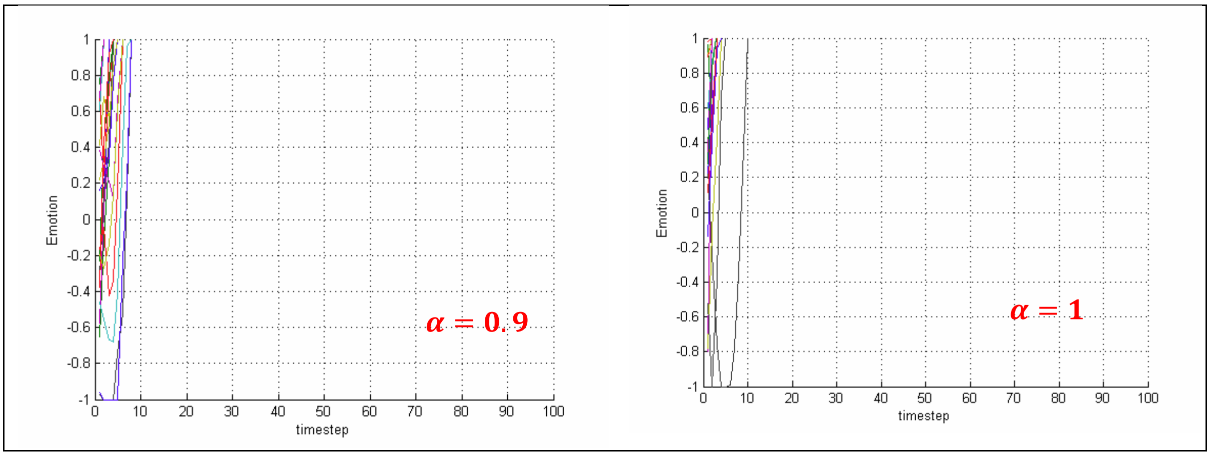


Figure (5) shows emotional-investors emotions changes with α for the uptrend price path shown in figure (6) were the other Cascade parameters β and γ were fixed at 0.35 , N=50 and m_0= 3

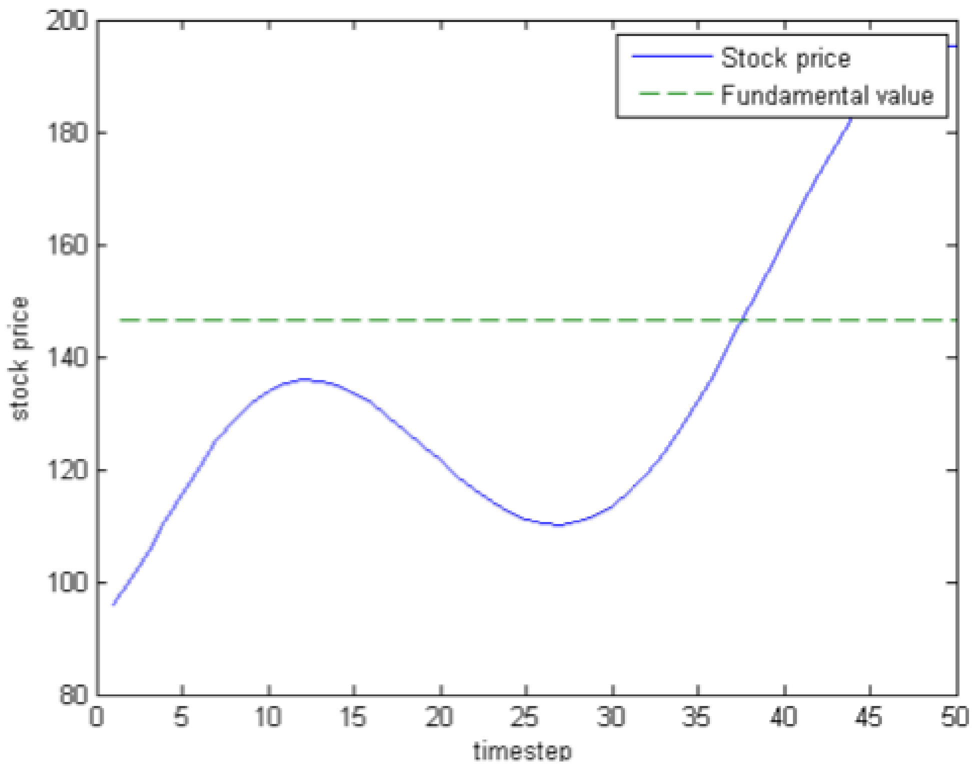
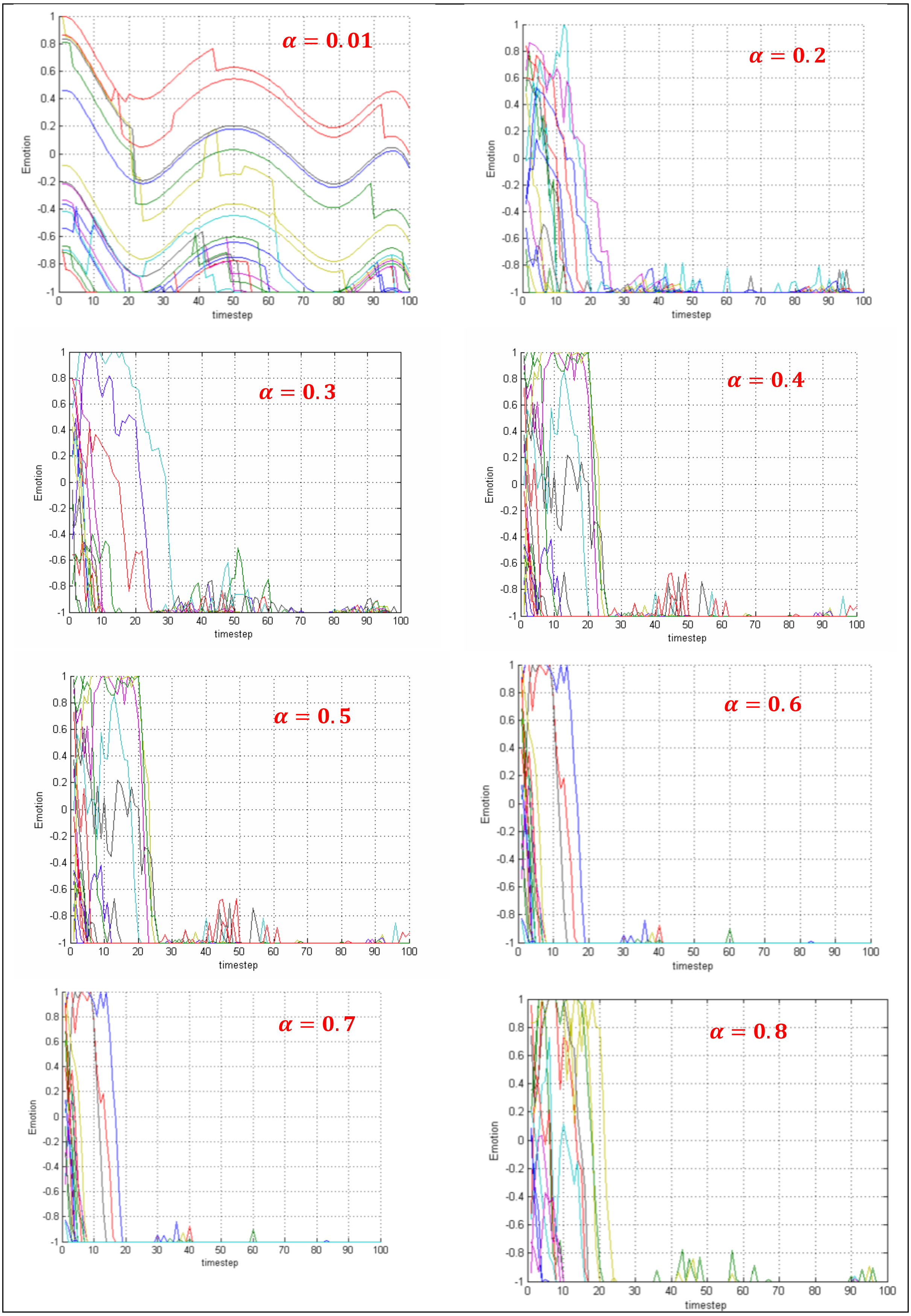


Figure (6) Up trend price path and its perceived fundament value at 0.75*peak value


$\alpha = 0.01$
$\alpha = 0.2$
$\alpha = 0.3$
$\alpha = 0.4$
$\alpha = 0.5$
$\alpha = 0.6$
$\alpha = 0.7$
$\alpha = 0.8$
Emotion
timestep

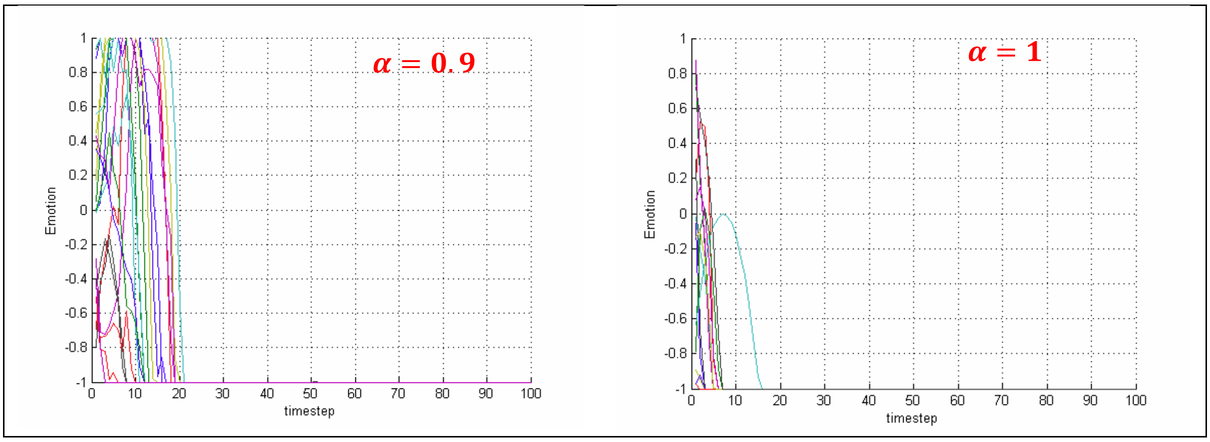


Figure (7) shows emotional-investors emotions changes with α for the downward price path shown in figure (8) were the other Cascade parameters β and γ were fixed at 0.35 , N=50 and m_0= 3

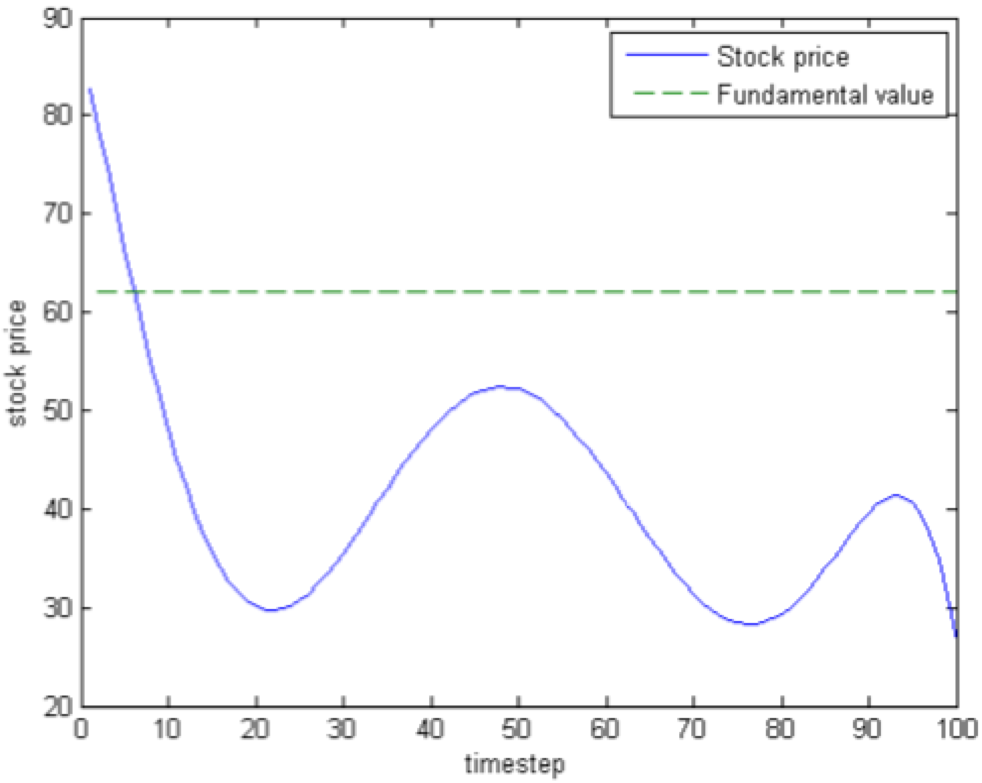
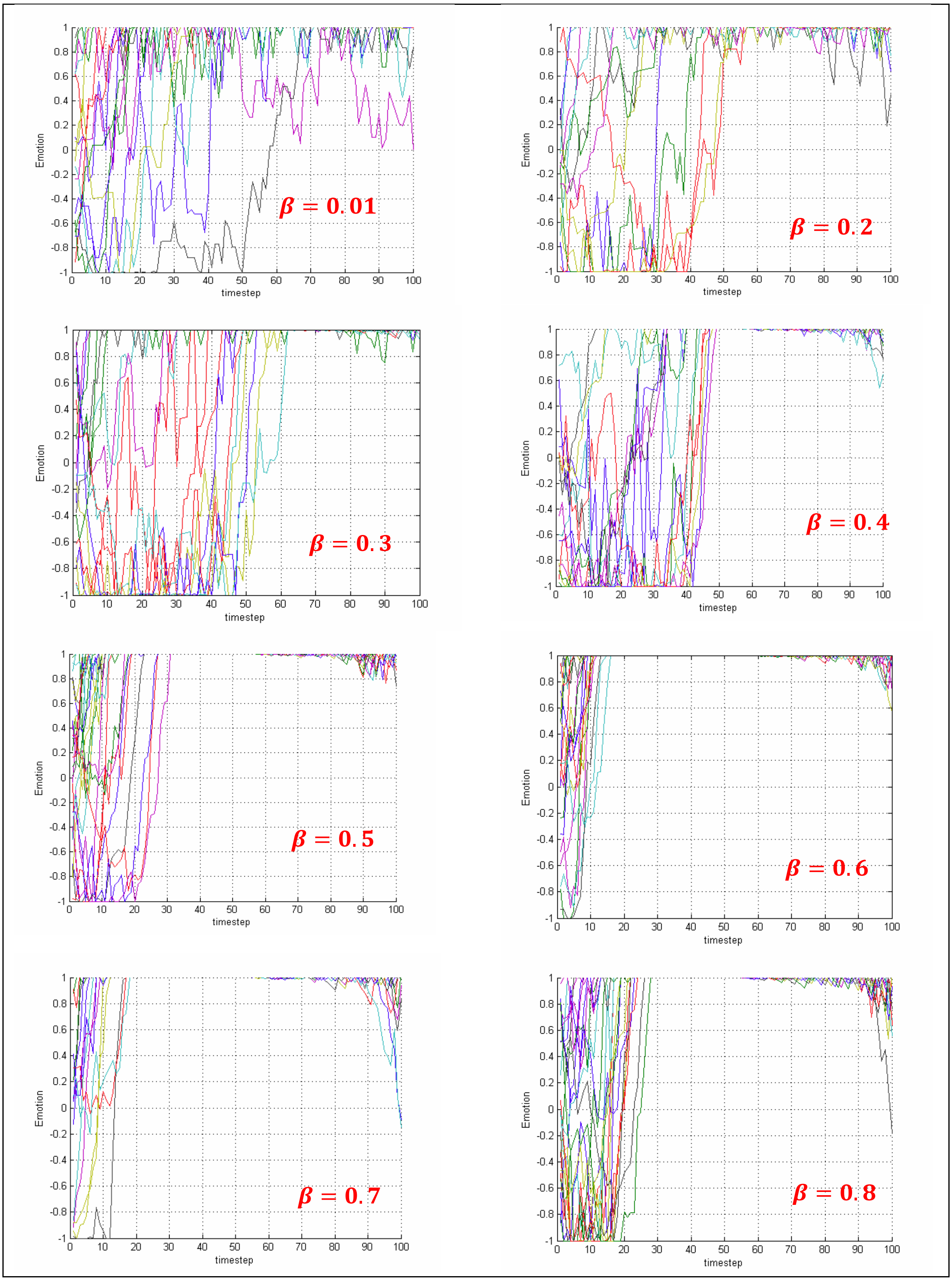


Figure (8) Downward price path and its perceived fundament value at 0.75*peak valu β = Emotional price history factor



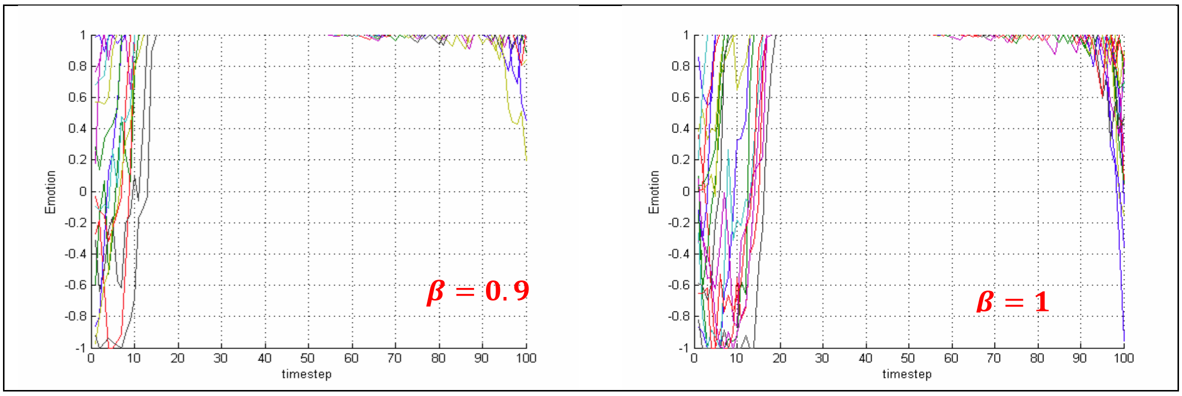
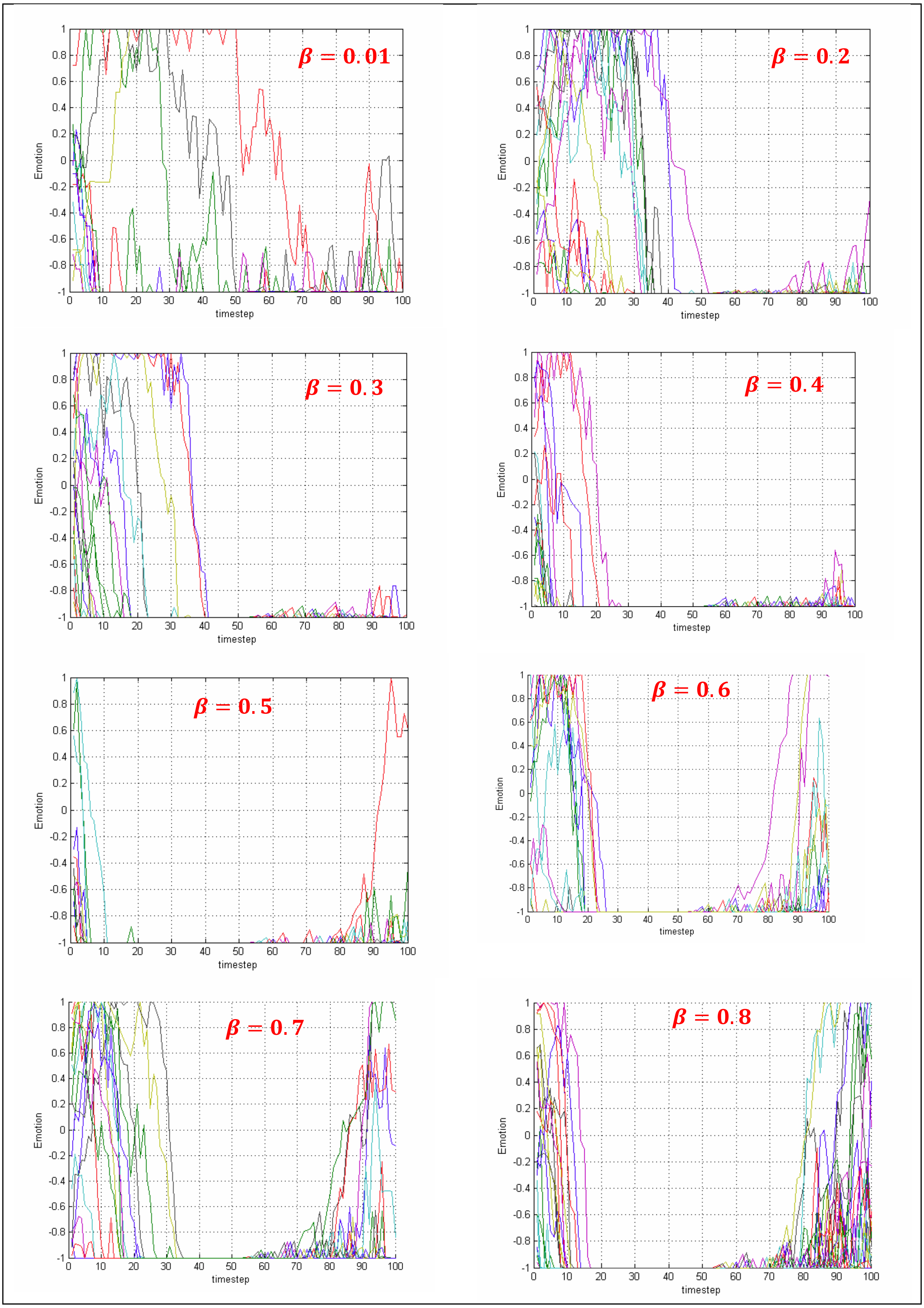


Figure (9) shows emotional-investors emotions changes with β for the n shape price path shown in figure (2) were the other Cascade parameters β and γ were fixed at 0.35 , N=50 and m_0= 3


$\beta = 0.01$
$\beta = 0.2$
$\beta = 0.3$
$\beta = 0.4$
$\beta = 0.5$
$\beta = 0.6$
$\beta = 0.7$
$\beta = 0.8$
Emotion
timestep

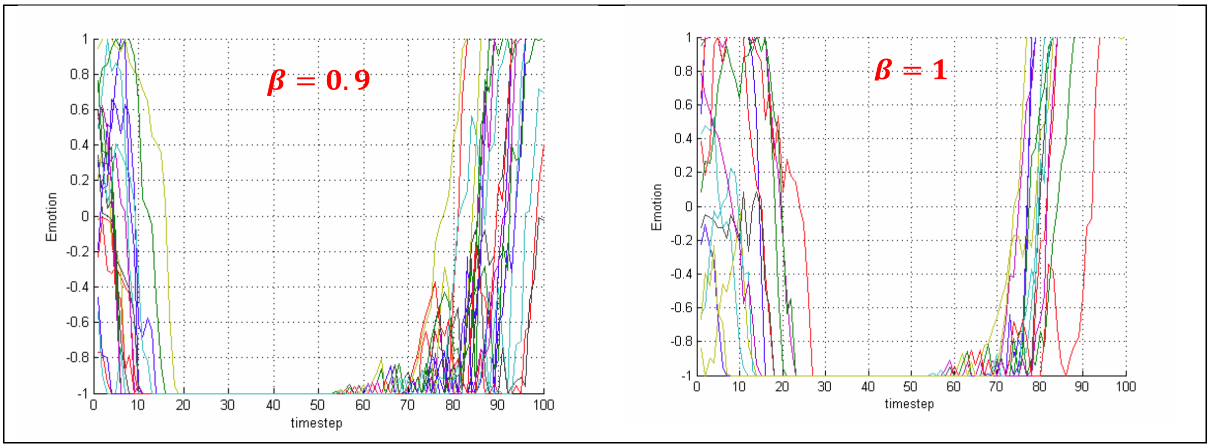
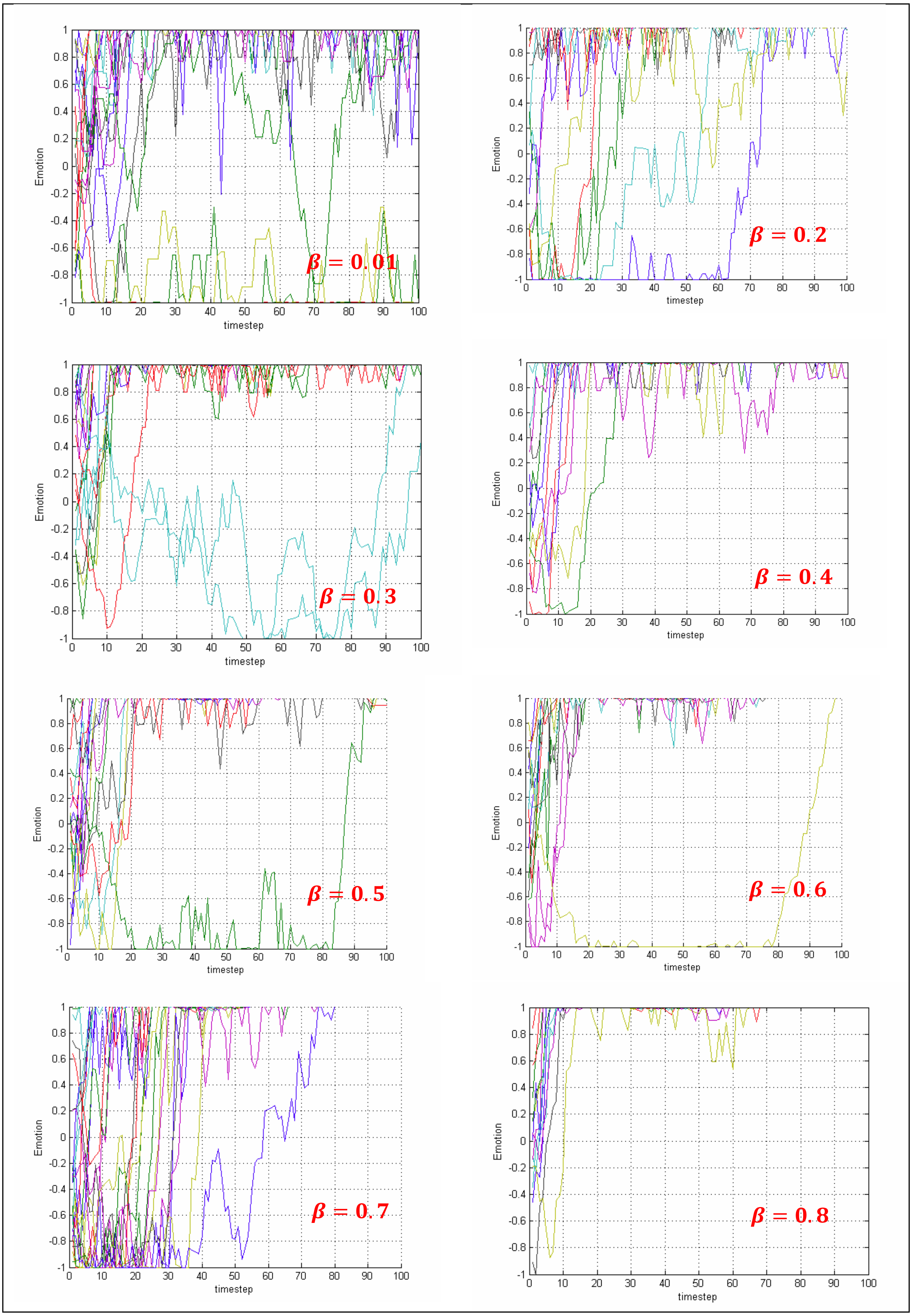


Figure (10) shows emotional-investors emotions changes with β for the u shape price path shown in figure (4) were the other Cascade parameters α and γ were fixed at 0.35 , N=50 and m_0= 3


Emotion
timestep
$\beta = 0.01$
Emotion
timestep
$\beta = 0.2$
Emotion
timestep
$\beta = 0.3$
Emotion
timestep
$\beta = 0.4$
Emotion
timestep
$\beta = 0.5$
Emotion
timestep
$\beta = 0.6$
Emotion
timestep
$\beta = 0.7$
Emotion
timestep
$\beta = 0.8$

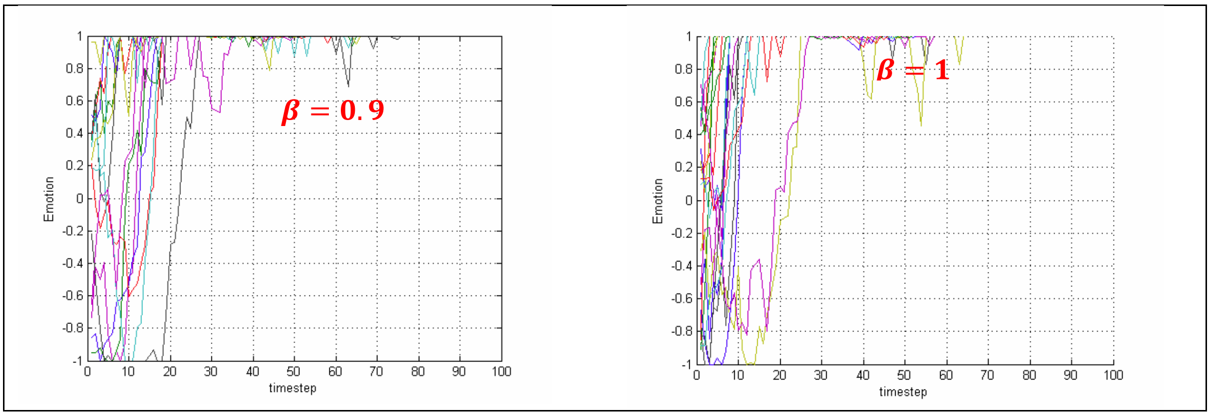
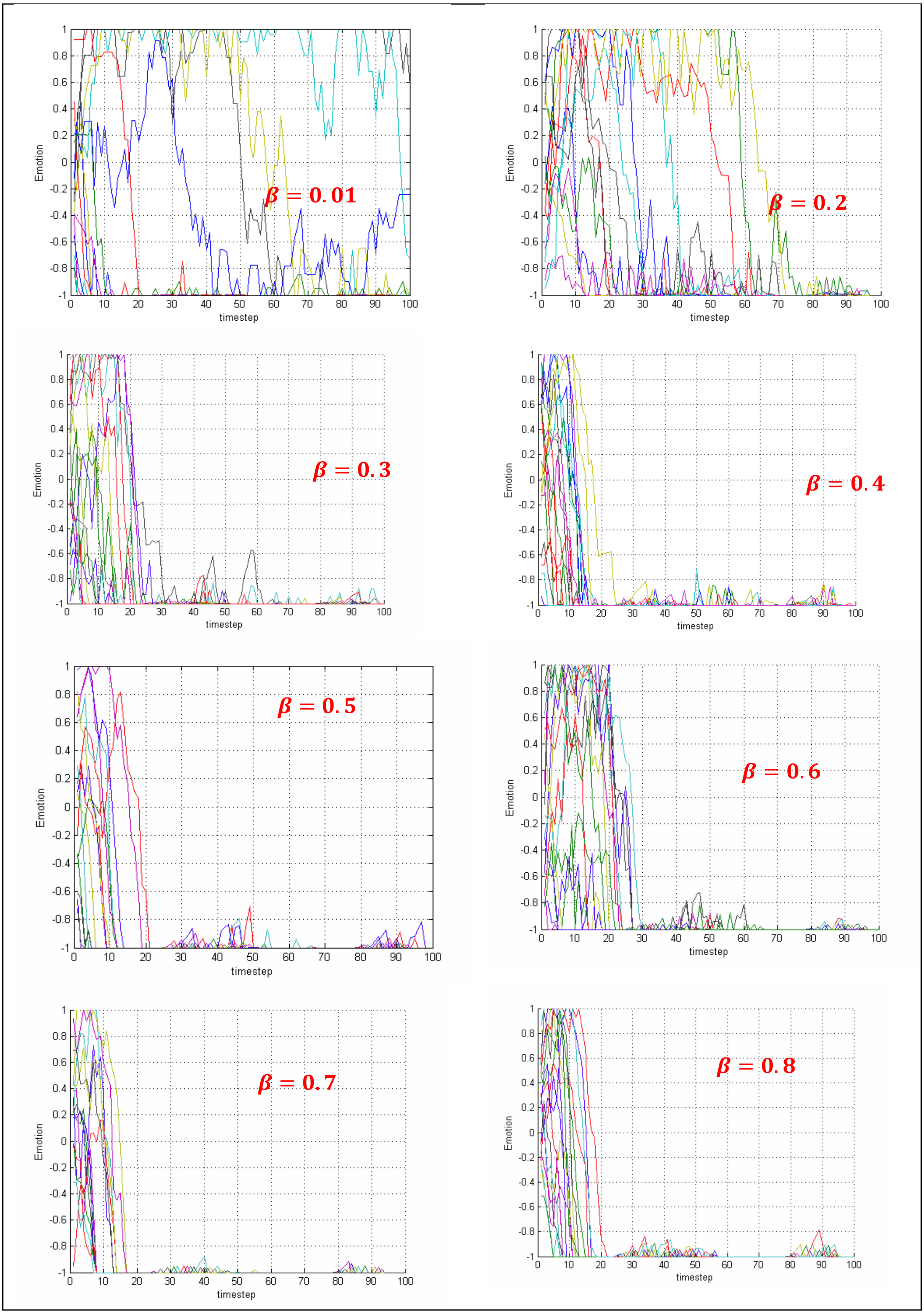


Figure (11) shows emotional-investors emotions changes with β for the upward price path shown in figure (6) were the other Cascade parameters α and γ were fixed at 0.35 , N=50 and m_0= 3


$\beta = 0.01$
$\beta = 0.2$
$\beta = 0.3$
$\beta = 0.4$
$\beta = 0.5$
$\beta = 0.6$
$\beta = 0.7$
$\beta = 0.8$
Emotion
timestep

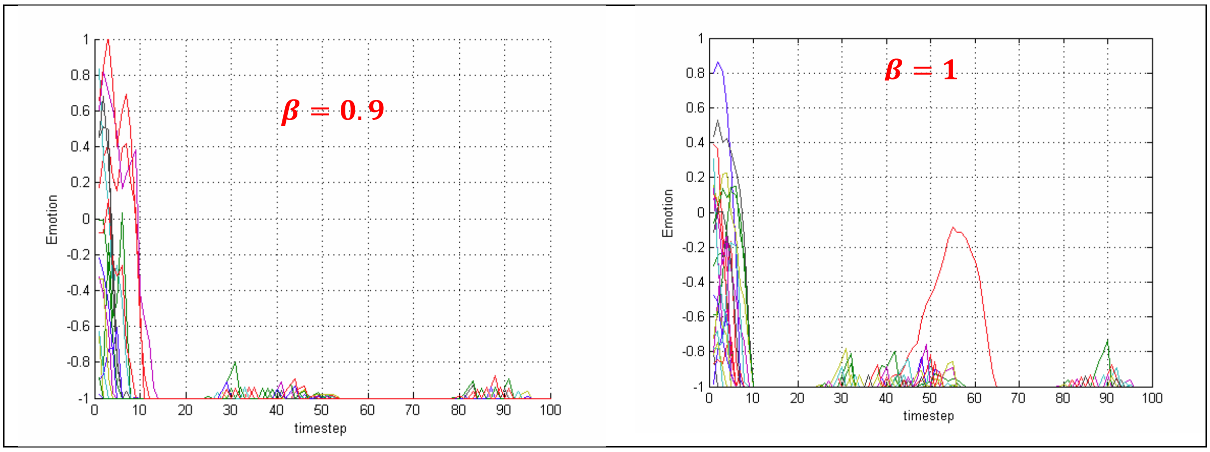
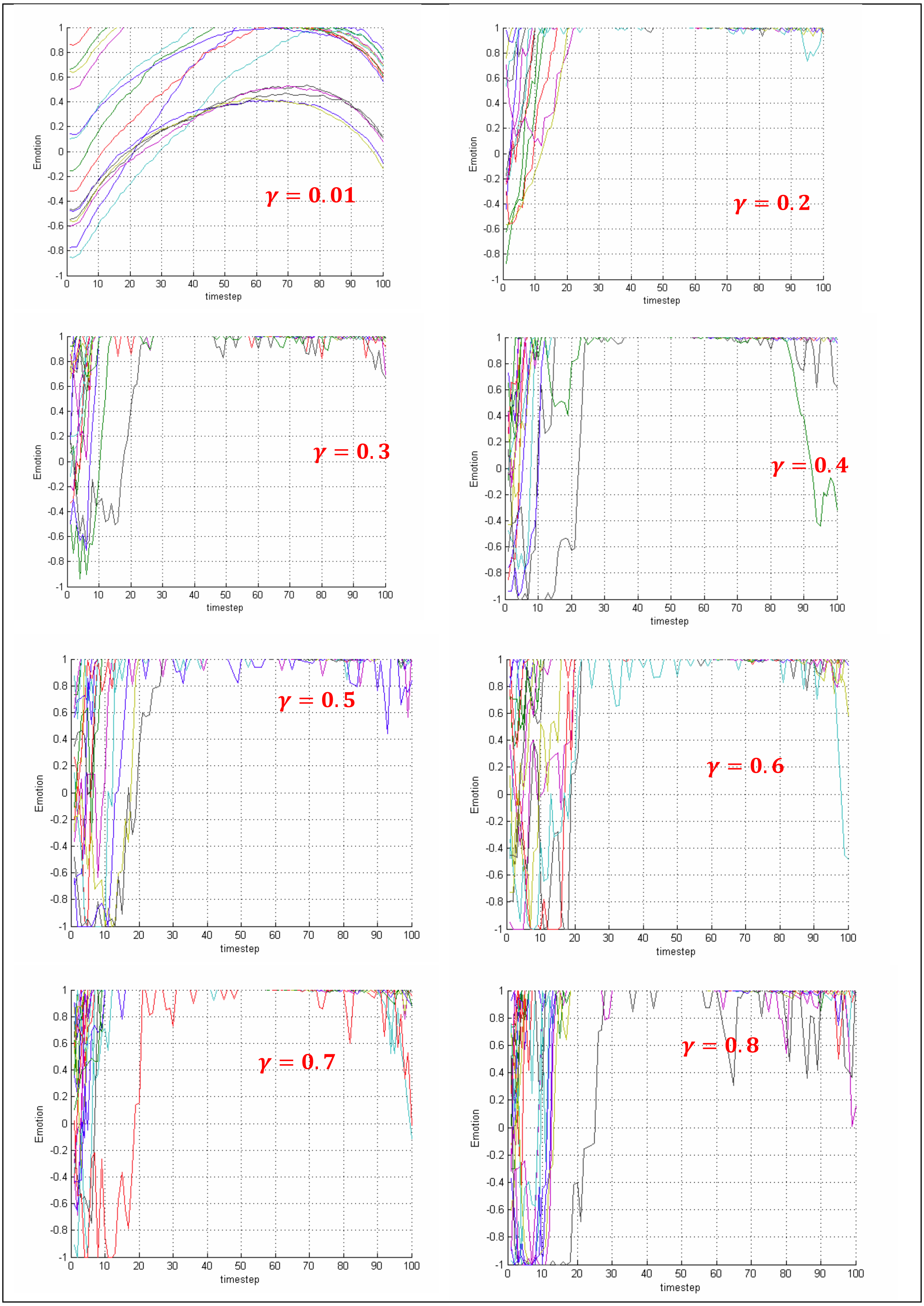


Figure (12) shows emotional-investors emotions changes with β for the downward price path shown in figure (8) were the other Cascade parameters α and γ were fixed at 0.35 , N=50 and m_0= 3

γ = Emotional propagation



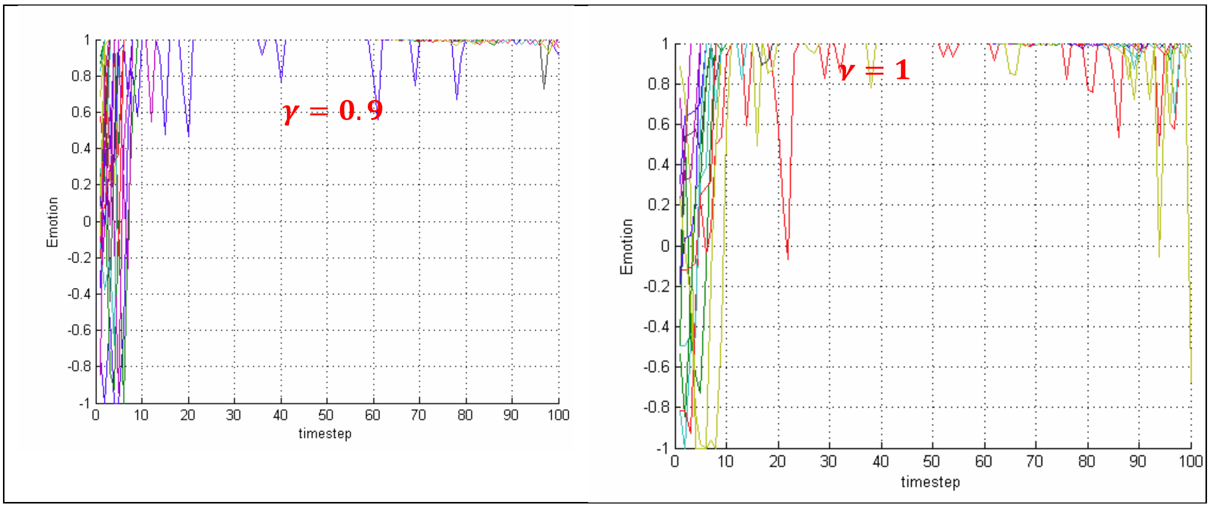
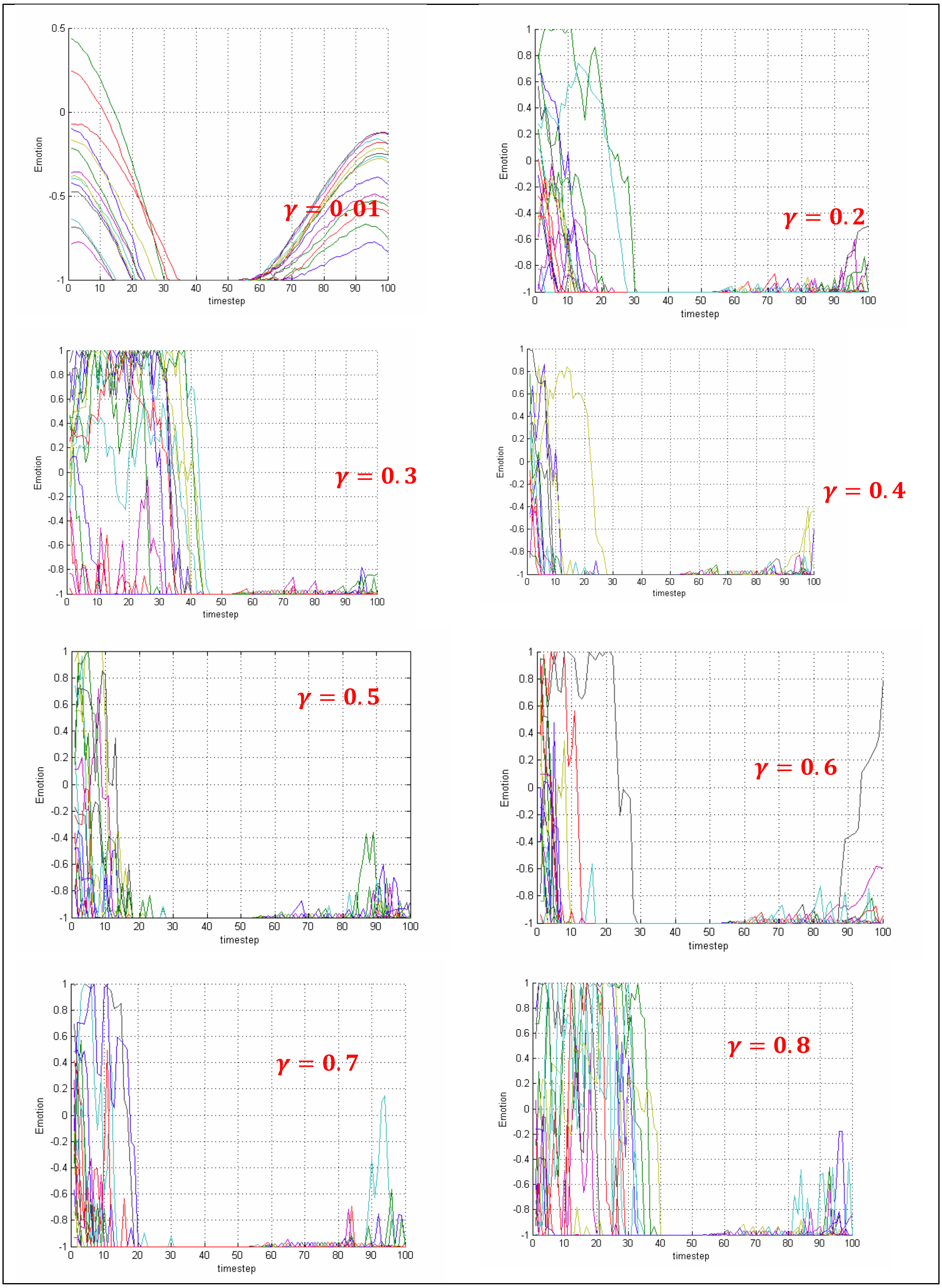


Figure (13) shows emotional-investors emotions changes with γ for the n shape price path shown in figure (2) were the other Cascade parameters α and β were fixed at 0.35 , N=50 and m_0= 3


$\gamma = 0.01$
$\gamma = 0.2$
$\gamma = 0.3$
$\gamma = 0.4$
$\gamma = 0.5$
$\gamma = 0.6$
$\gamma = 0.7$
$\gamma = 0.8$
Emotion
timestep

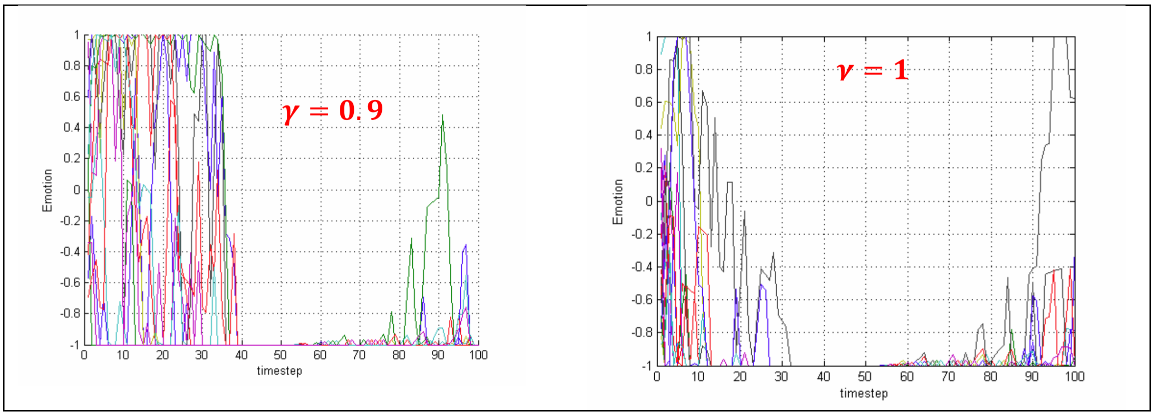
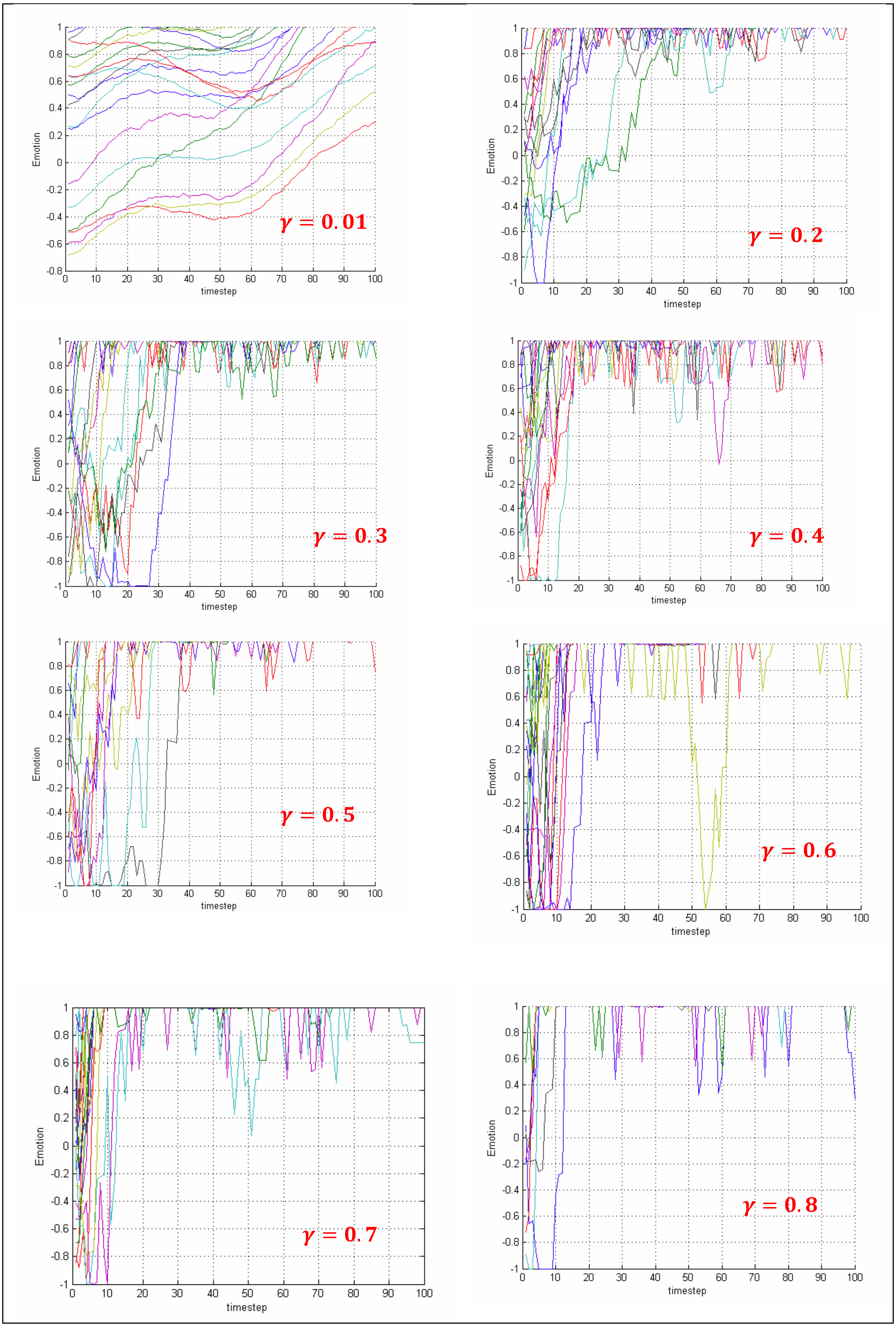


Figure (14) shows emotional-investors emotions changes with γ the u shape price path shown in figure (4) were the other Cascade parameters α and β were fixed at 0.35 , N=50 and m_0= 3


Emotion
timestep
$\gamma = 0.01$
$\gamma = 0.2$
$\gamma = 0.3$
$\gamma = 0.4$
$\gamma = 0.5$
$\gamma = 0.6$
$\gamma = 0.7$
$\gamma = 0.8$

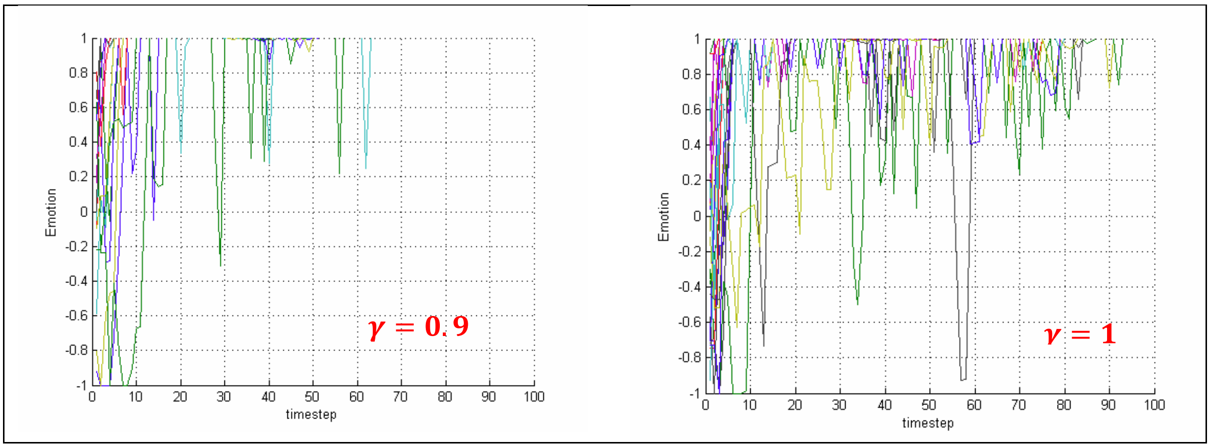
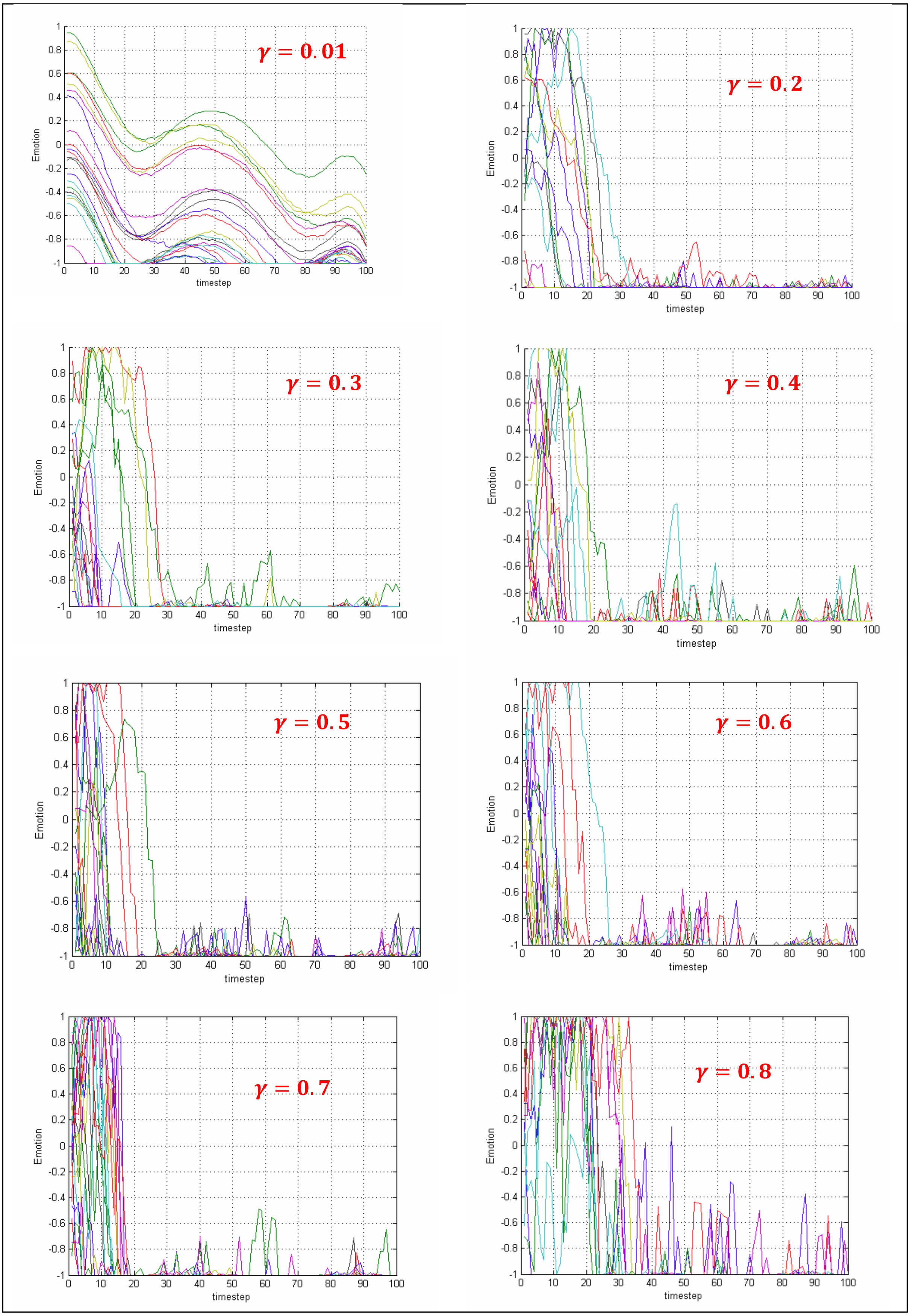


Figure (15) shows emotional-investors emotions changes with γ for the upward price path shown in figure (6) were the other Cascade parameters α and β were fixed at 0.35 , N=50 and m_0= 3


γ = 0.01
γ = 0.2
γ = 0.3
γ = 0.4
γ = 0.5
γ = 0.6
γ = 0.7
γ = 0.8
Emotion
timestep

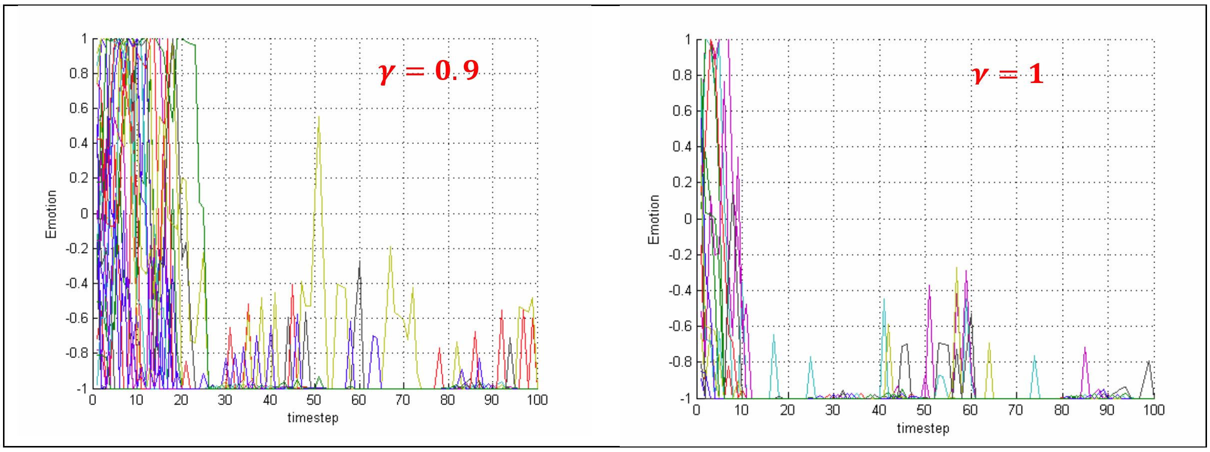


Figure (16) shows emotional-investors emotions changes with γ for the downward price path shown in figure (8) were the other Cascade parameters α and β were fixed at 0.35 , N=50 and m_0= 3

Minimum number of connections (m_0)

In the section we analyse the minimum number of concoction and the emotional cascade process , we will demonstrate this using circular contour plot. Where nodes in the first circle –the largest one- represent nodes with one connection and the nodes with higher node degree represented larger and closer to the centre, see figure 17

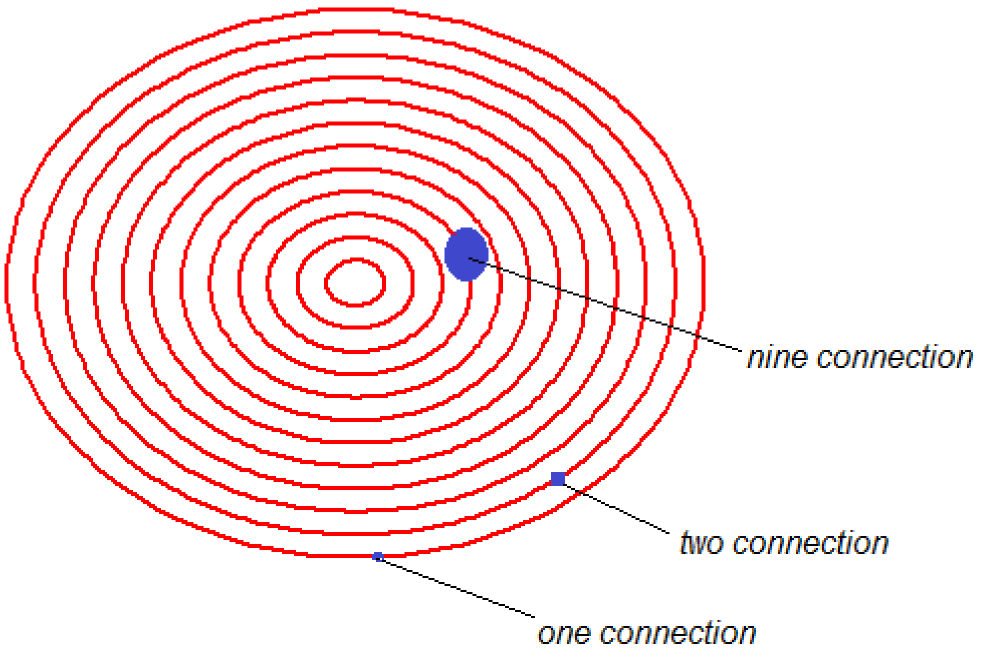
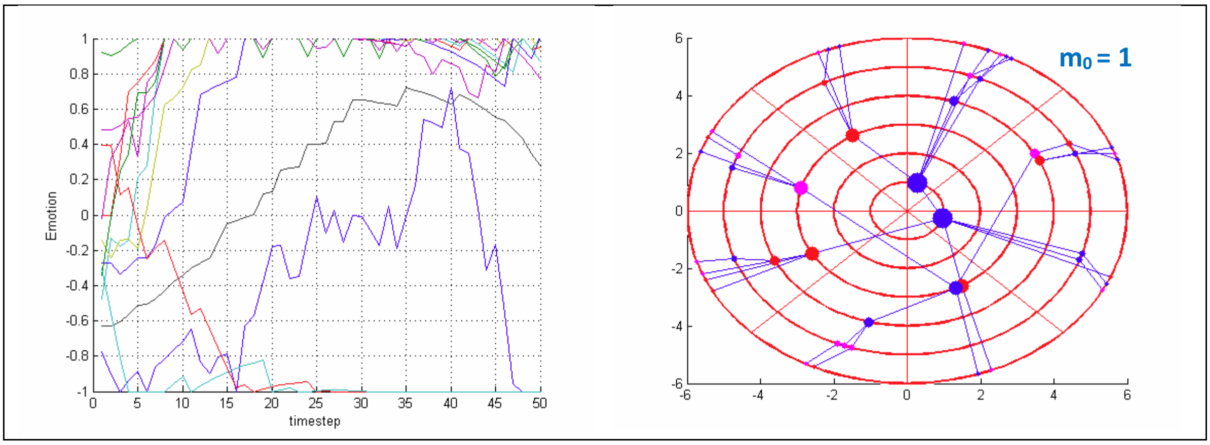


Figure 17 contour plot to represent investor's node degree.



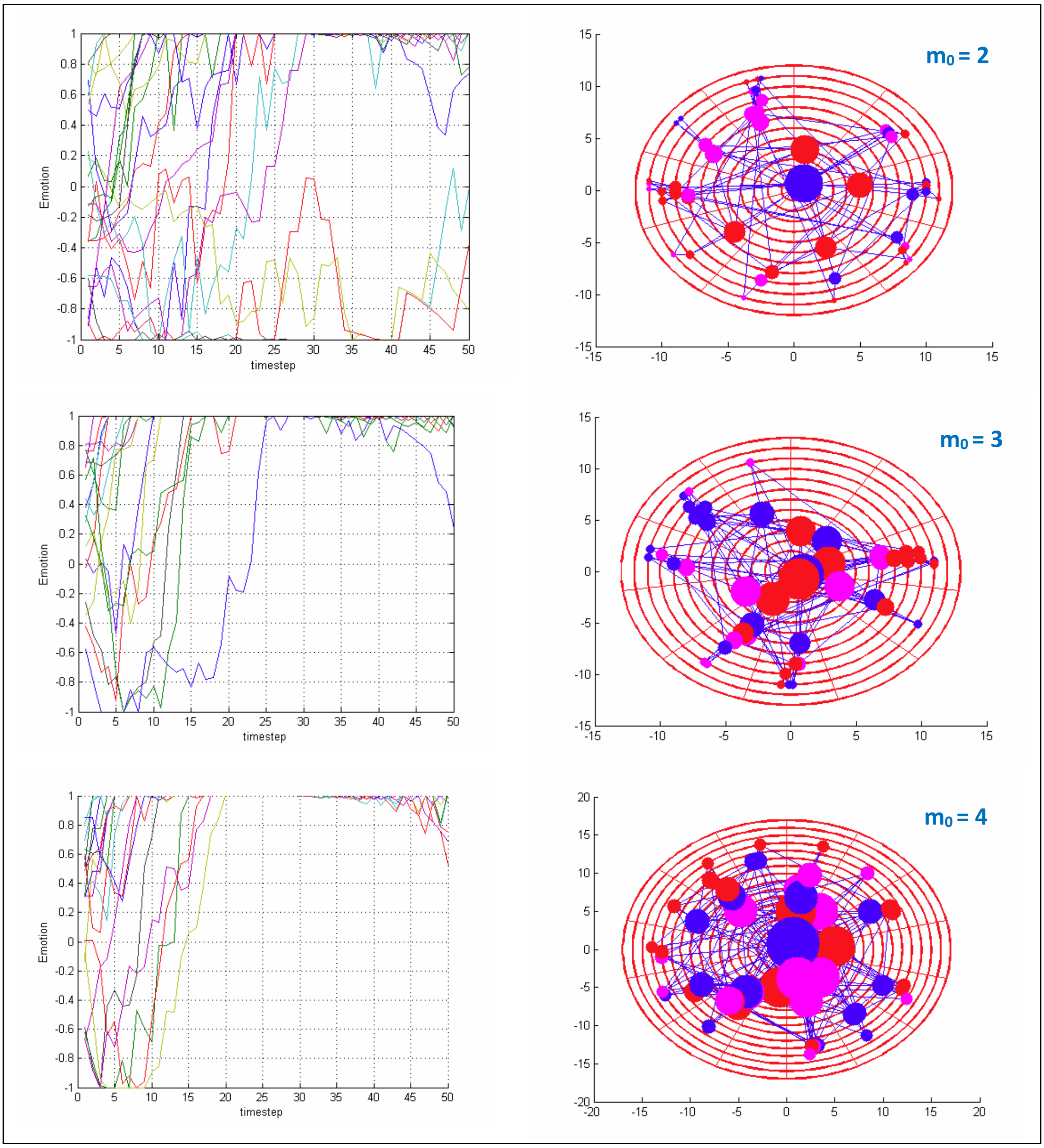
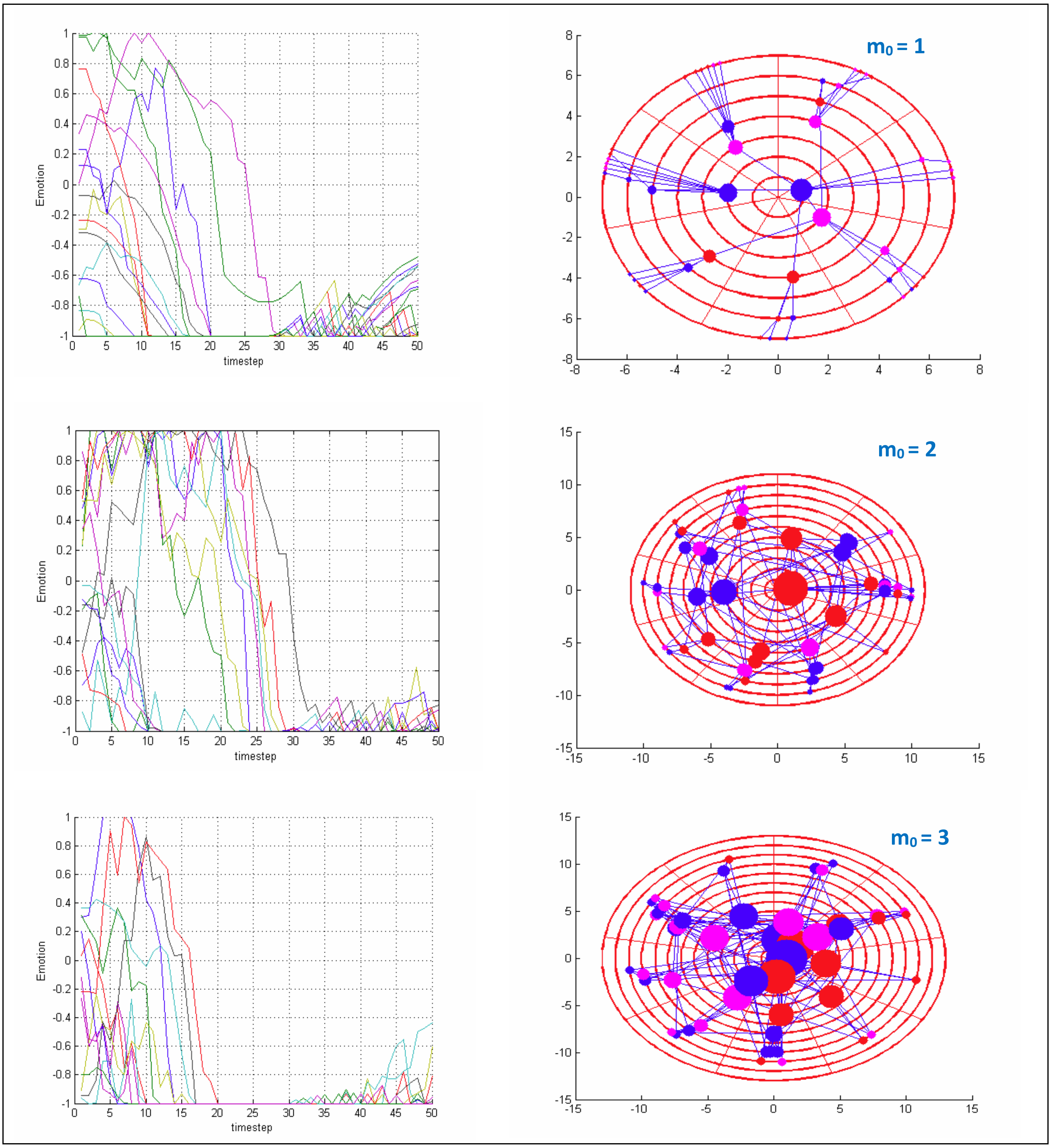


Figure (18) shows emotional-investors emotions changes as the minimum number of connection changes from 1 to 4 for the n shape price path shown in figure (2) were the other Cascade parameters α , β and γ were fixed at 0.35 and N=50 .



Emotion
timestep
$m_0 = 1$
$m_0 = 2$
$m_0 = 3$

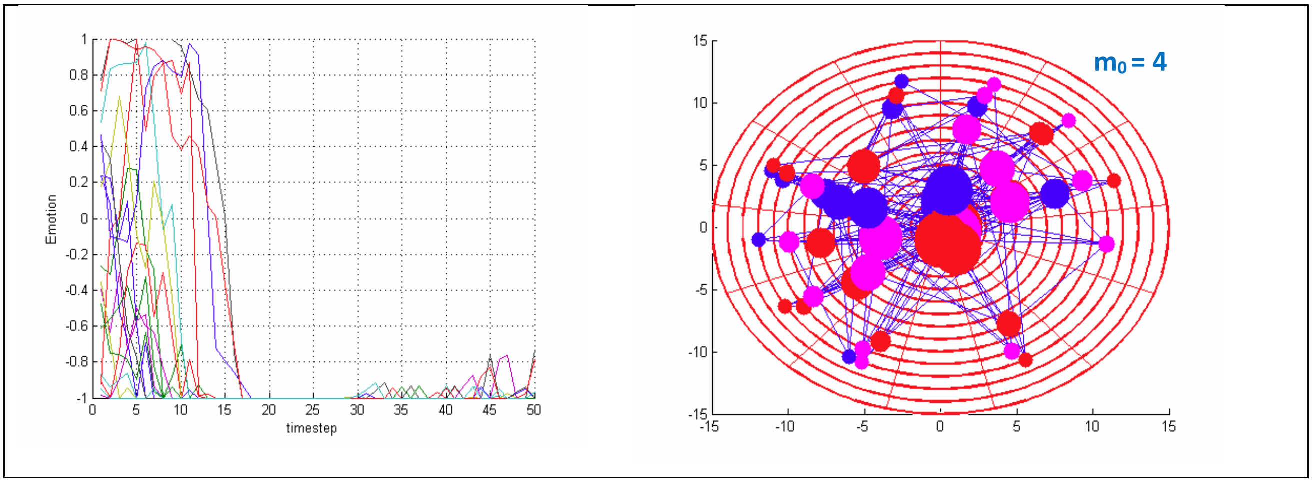


Figure (19) shows emotional-investors emotions changes as the minimum number of connection changes from 1 to 4 for the u shape price path shown in figure (4) were the other Cascade parameters α , β and γ were fixed at 0.35 and N=50 .

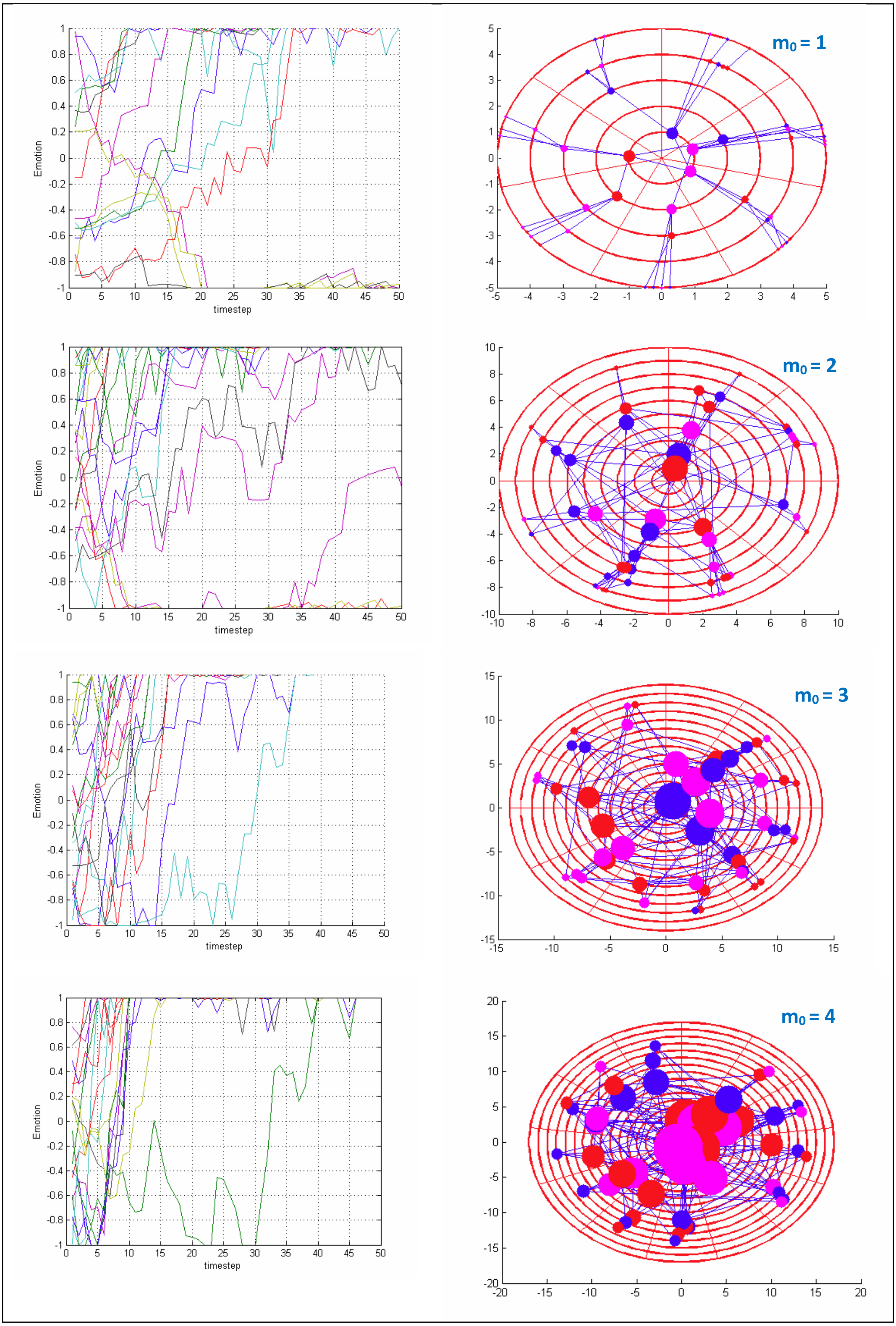
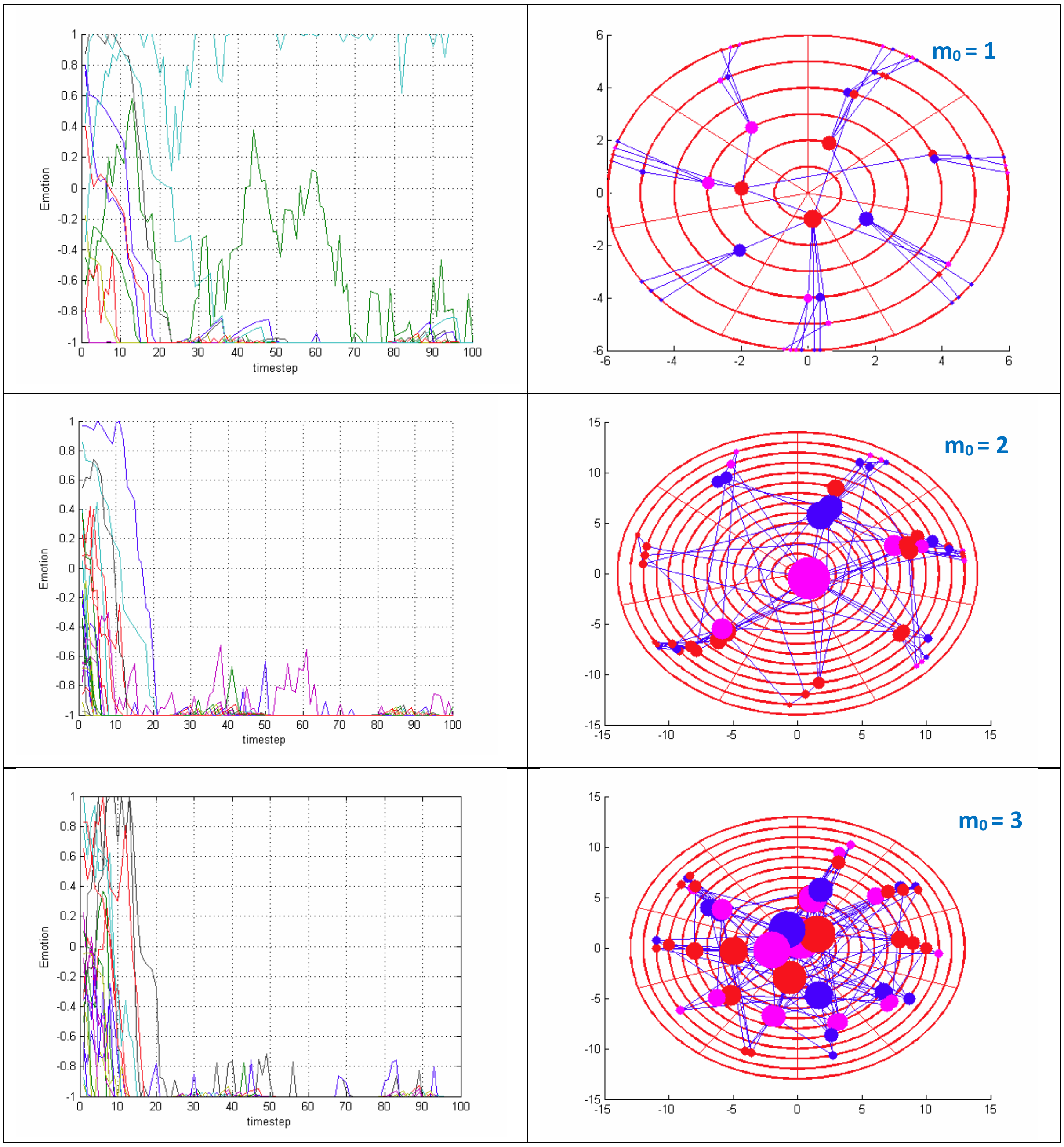

Emotion
timestep
$m_0 = 1$
Emotion
timestep
$m_0 = 2$
Emotion
timestep
$m_0 = 3$
Emotion
timestep
$m_0 = 4$

Figure (20) shows emotional-investors emotions changes as the minimum number of connection changes from 1 to 4 for the upward price path shown in figure (6) were the other Cascade parameters α , β and γ were fixed at 0.35 and N=50 .



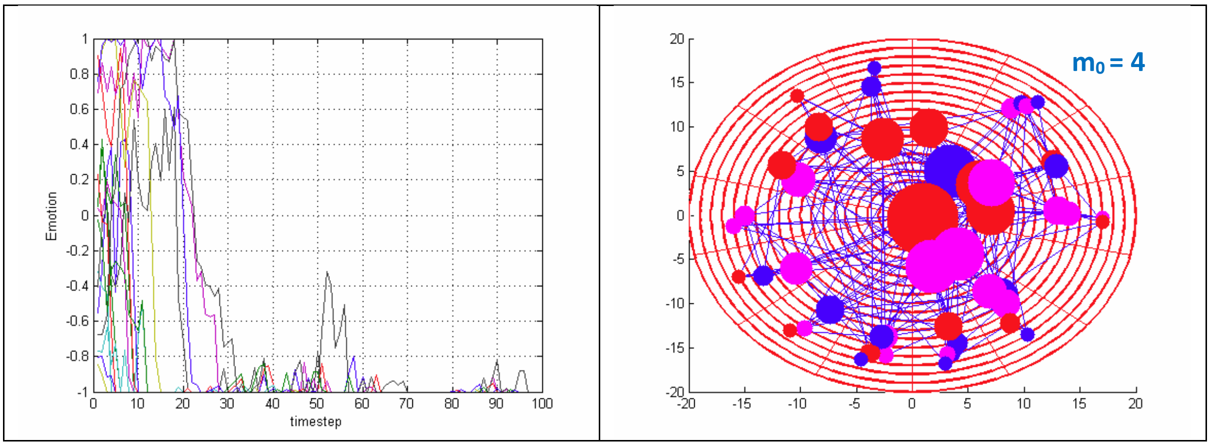


Figure (21) shows emotional-investors emotions changes as the minimum number of connection changes from 1 to 4 for the downward price path shown in figure (8) were the other Cascade parameters α , β and γ were fixed at 0.35 and N=50 .

Size of network

In the section we analyse the size of the network and it is impact on the emotion cascade process.

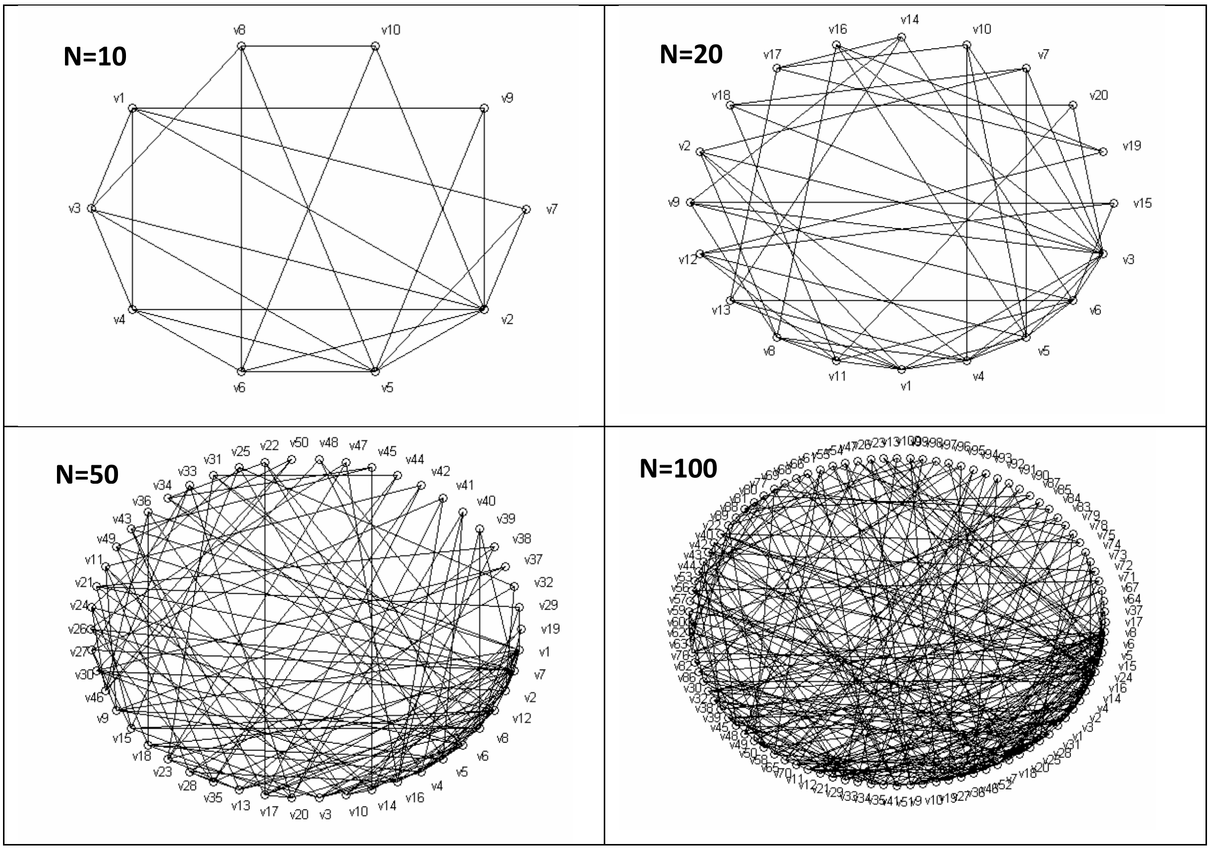


Figure (22) Freescale network generated with minimum of 3 connection with size shown.

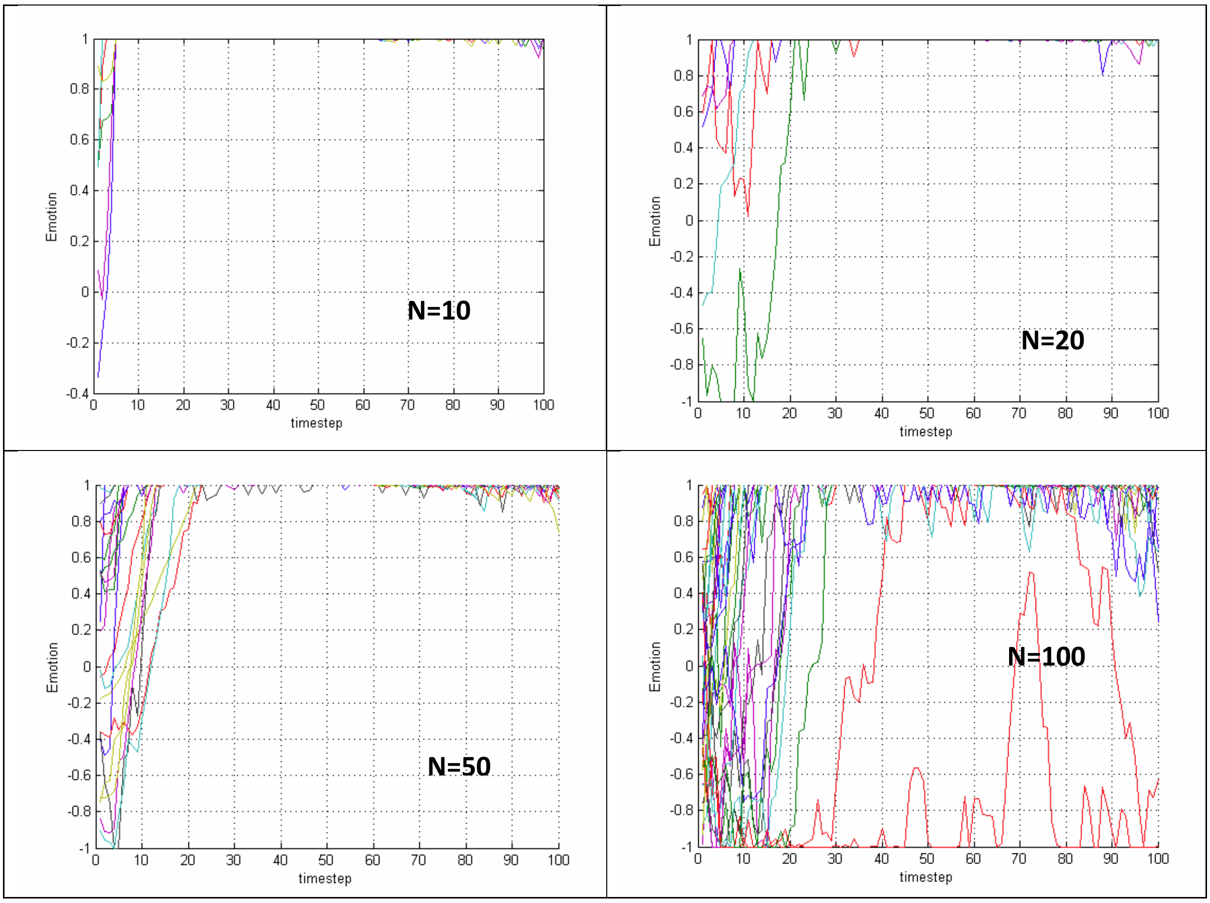


Figure (23) shows emotional-investors emotions changes as the size of the network changes from 10 to 100 for the n shape path shown in figure (2) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 .

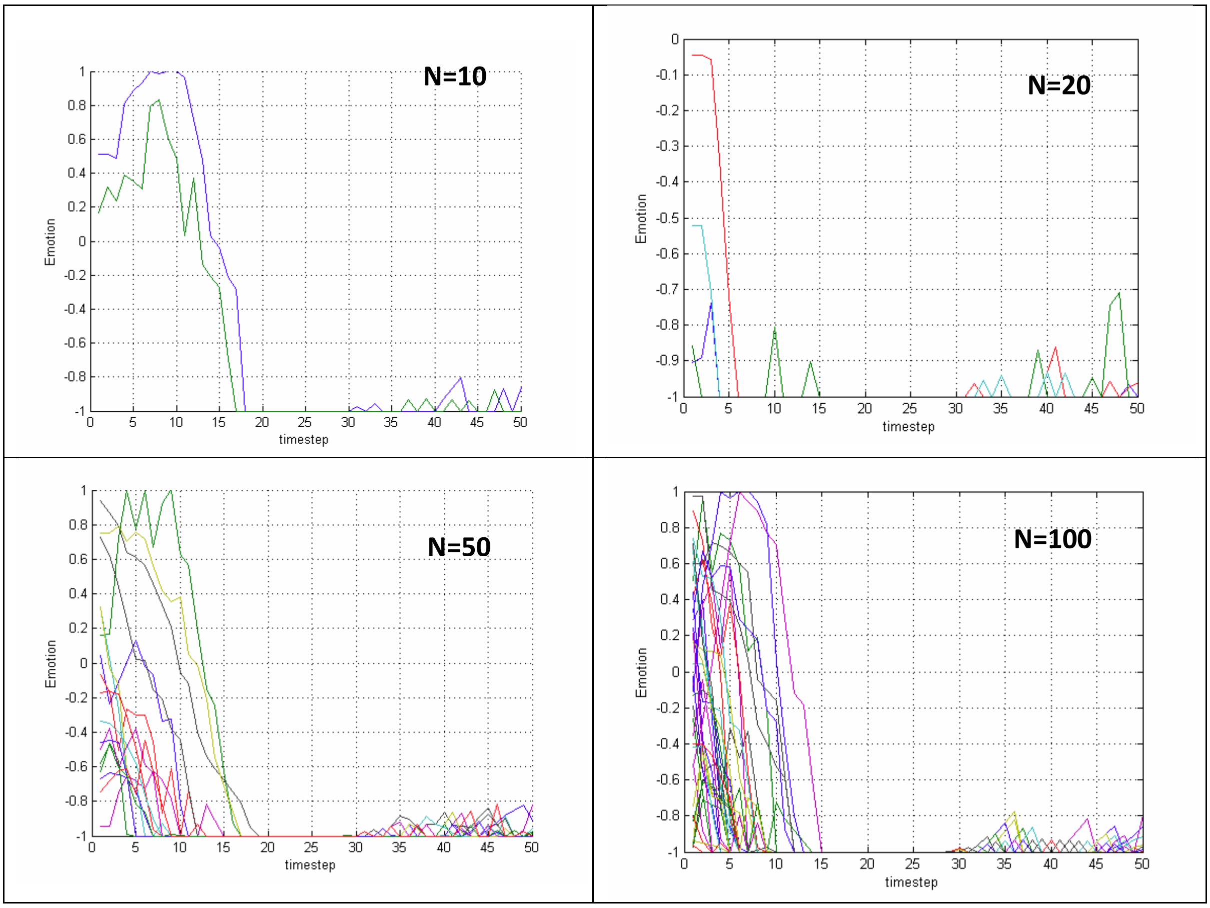


Figure (24) shows emotional-investors emotions changes as the size of the network changes from 10 to 100 for the u shape path shown in figure (4) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 .

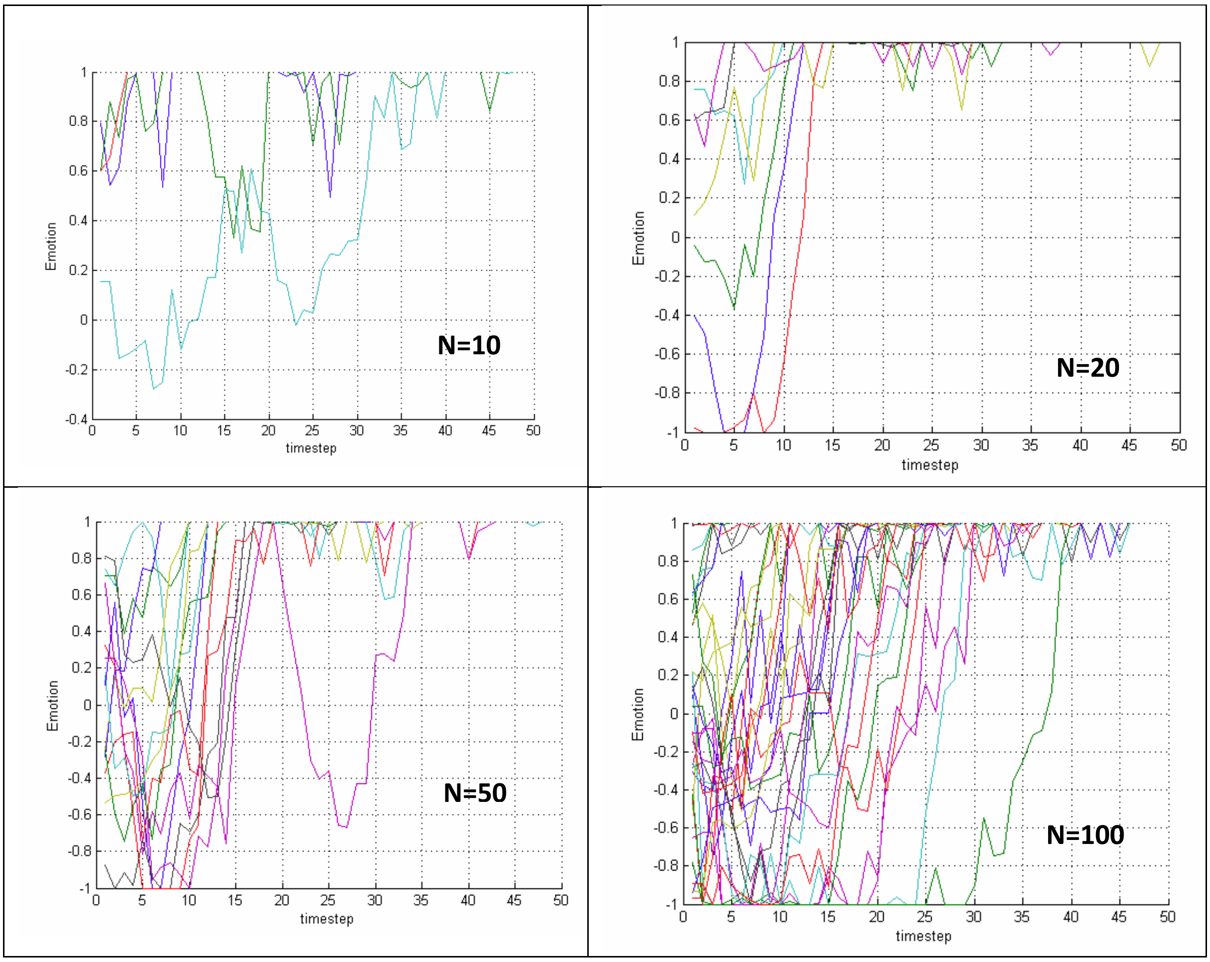


Figure (25) shows emotional-investors emotions changes as the size of the network changes from 10 to 100 for the upward price path shown in figure (6) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 .

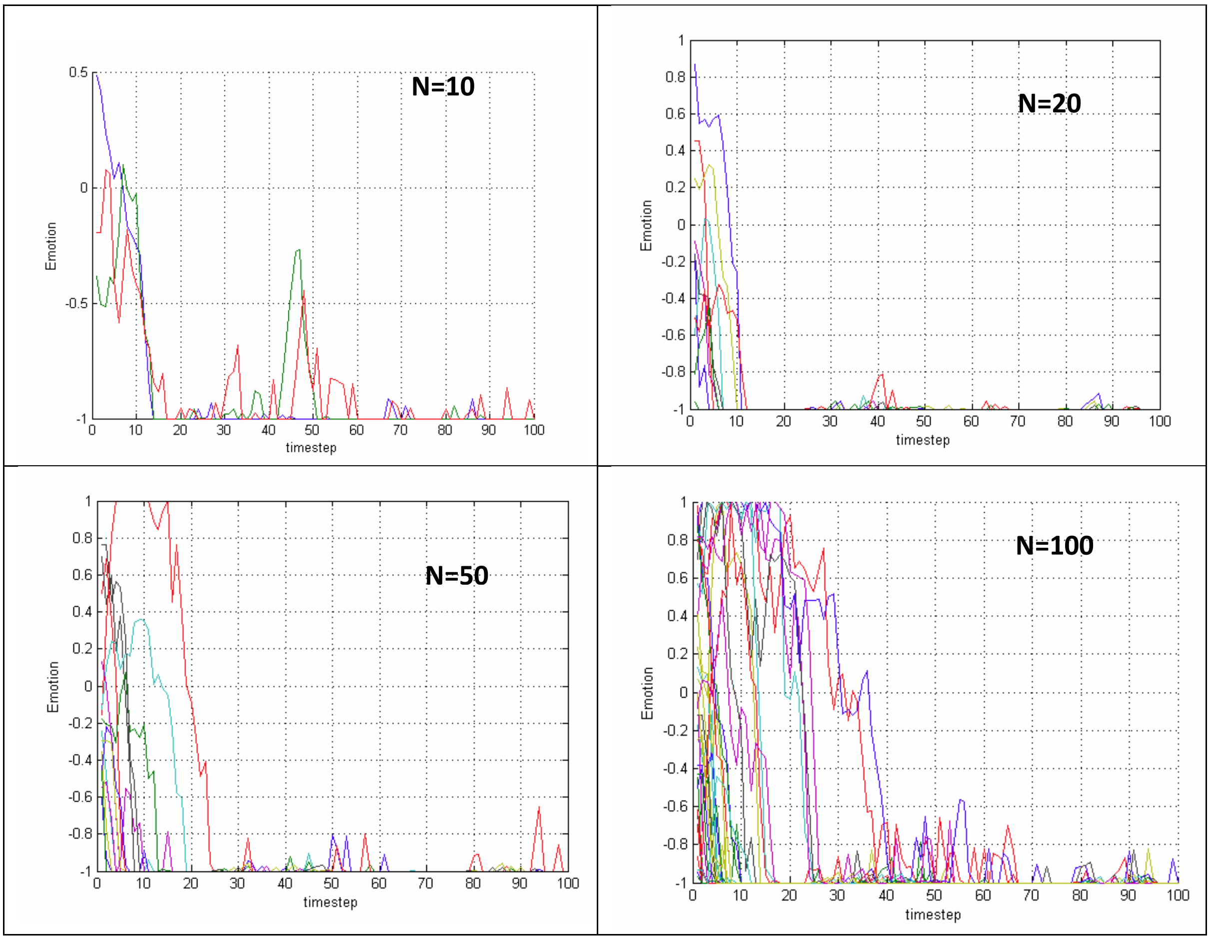
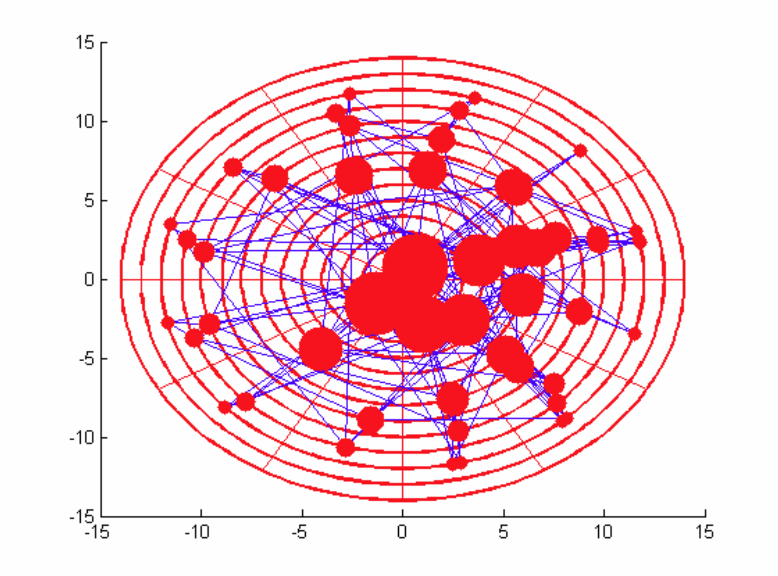


Figure (26) shows emotional-investors emotions changes as the size of the network changes from 10 to 100 for the downward price path shown in figure (8) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 .

Percentage of emotional to semi-emotional and Rational Investors

In the previous work we conducted the analysis using equal split between the three types of investors of interest i.e. 1/3. In the section we conduct analysis using different combination of split. And we observe how emotion and wealth change over time and different price path.

-First for network with 100% emotional investors.



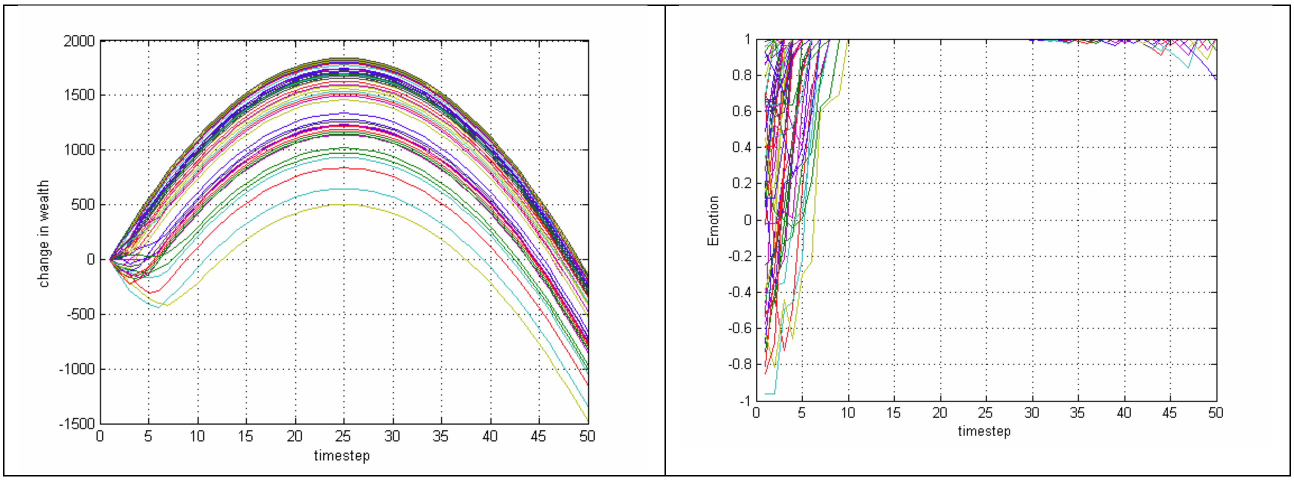


Figure (27) shows emotional-investors emotions and wealth changes for the n shape price path shown in figure (2) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50 .

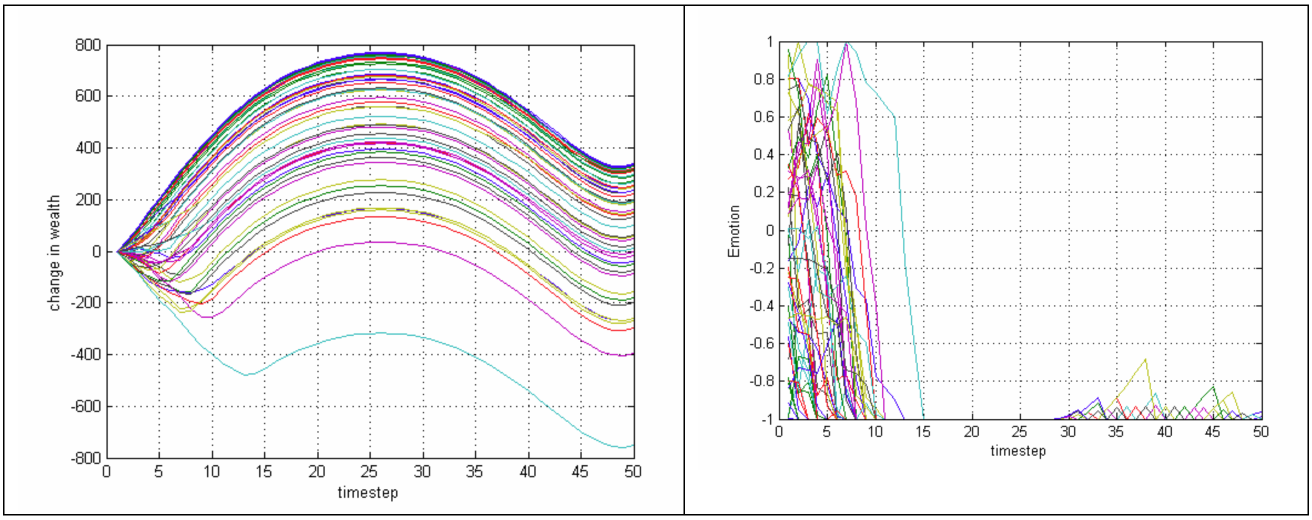


Figure (28) shows emotional-investors emotions and wealth changes for the u shape price path shown in figure (4) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50 .

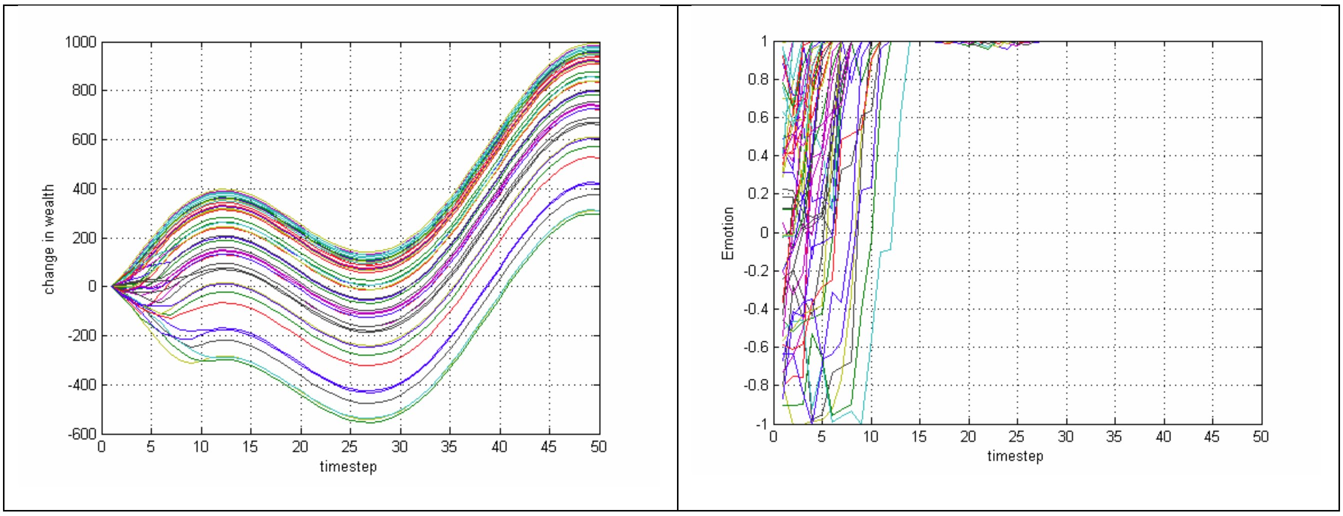


Figure (29) shows emotional-investors emotions and wealth changes for the upward price path shown in figure (6) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50 .

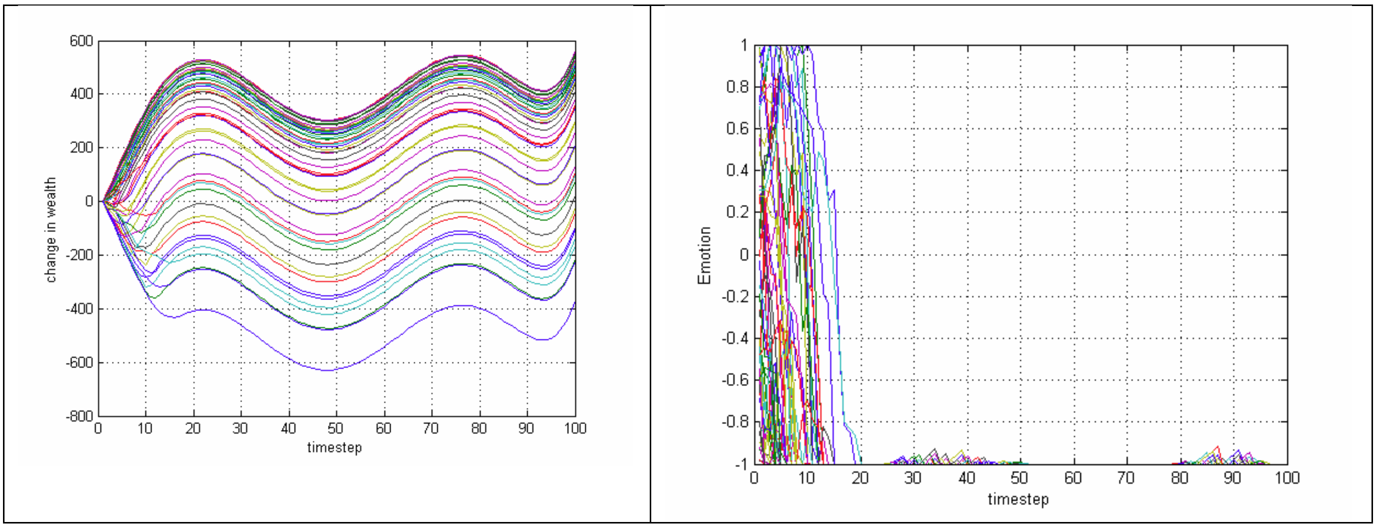
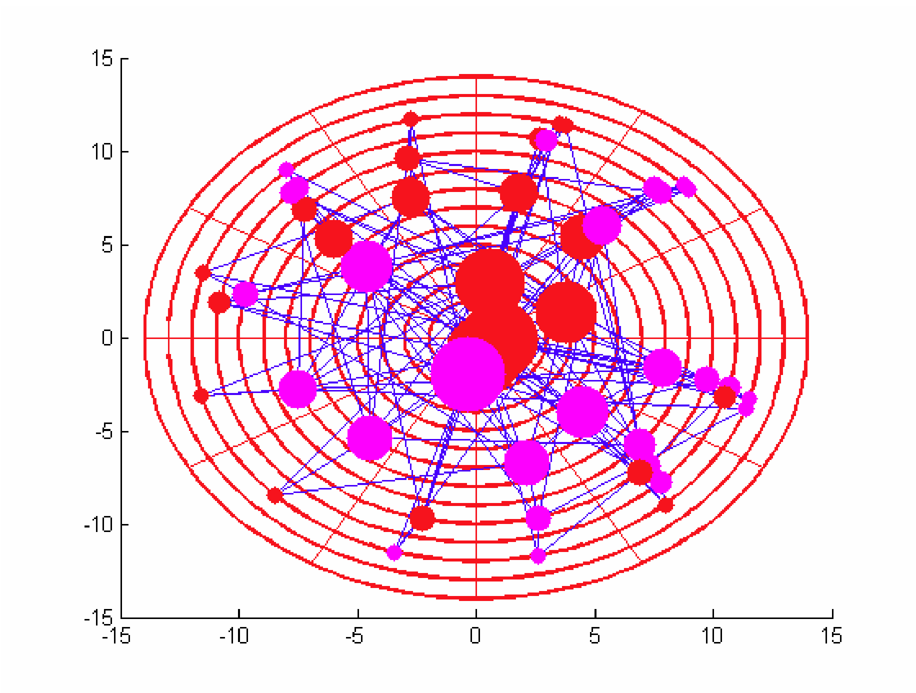


Figure (30) shows emotional-investors emotions and wealth changes for the downward price path shown in figure (8) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50 .

-Second for network with 50/50 emotional/semi-emotional investors.



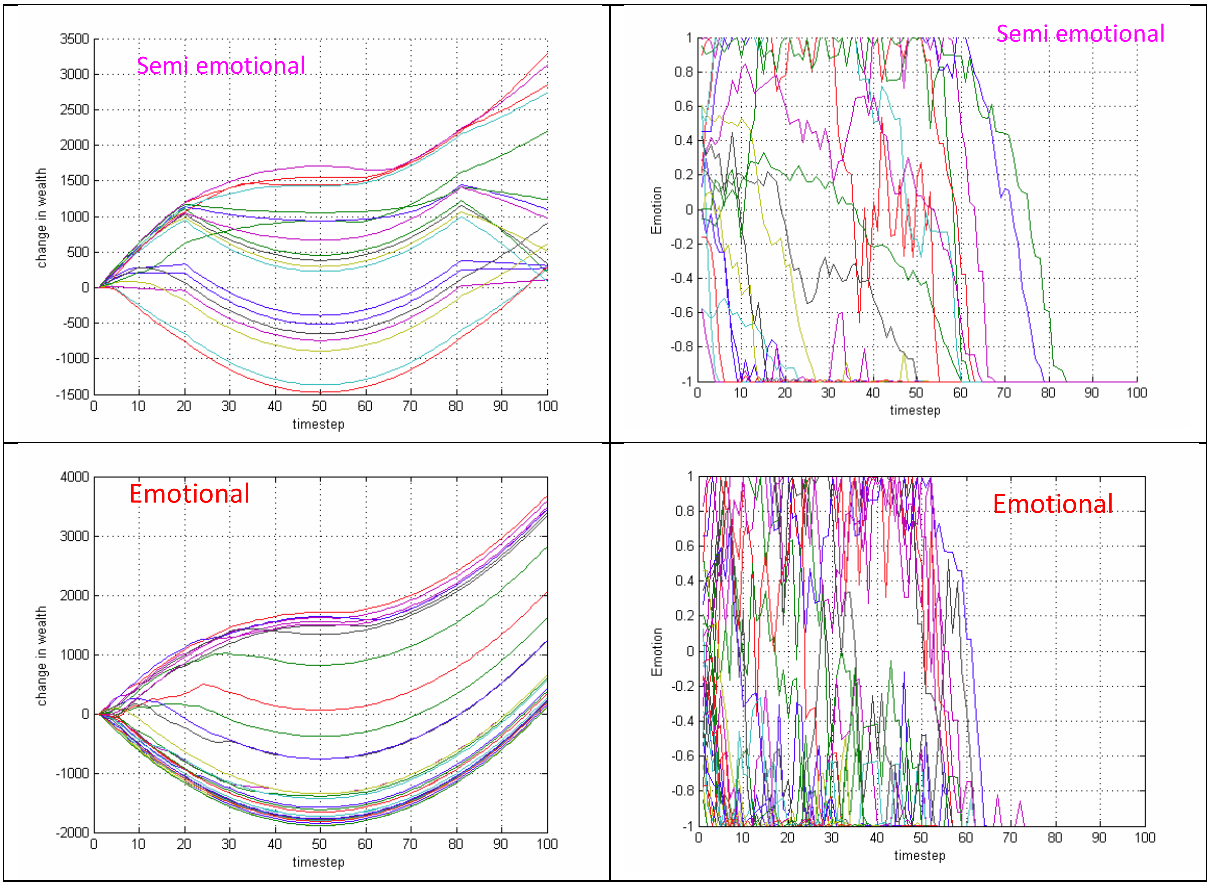


Figure (31) shows investors emotions and wealth changes for the n shape price path shown in figure (2) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50 .

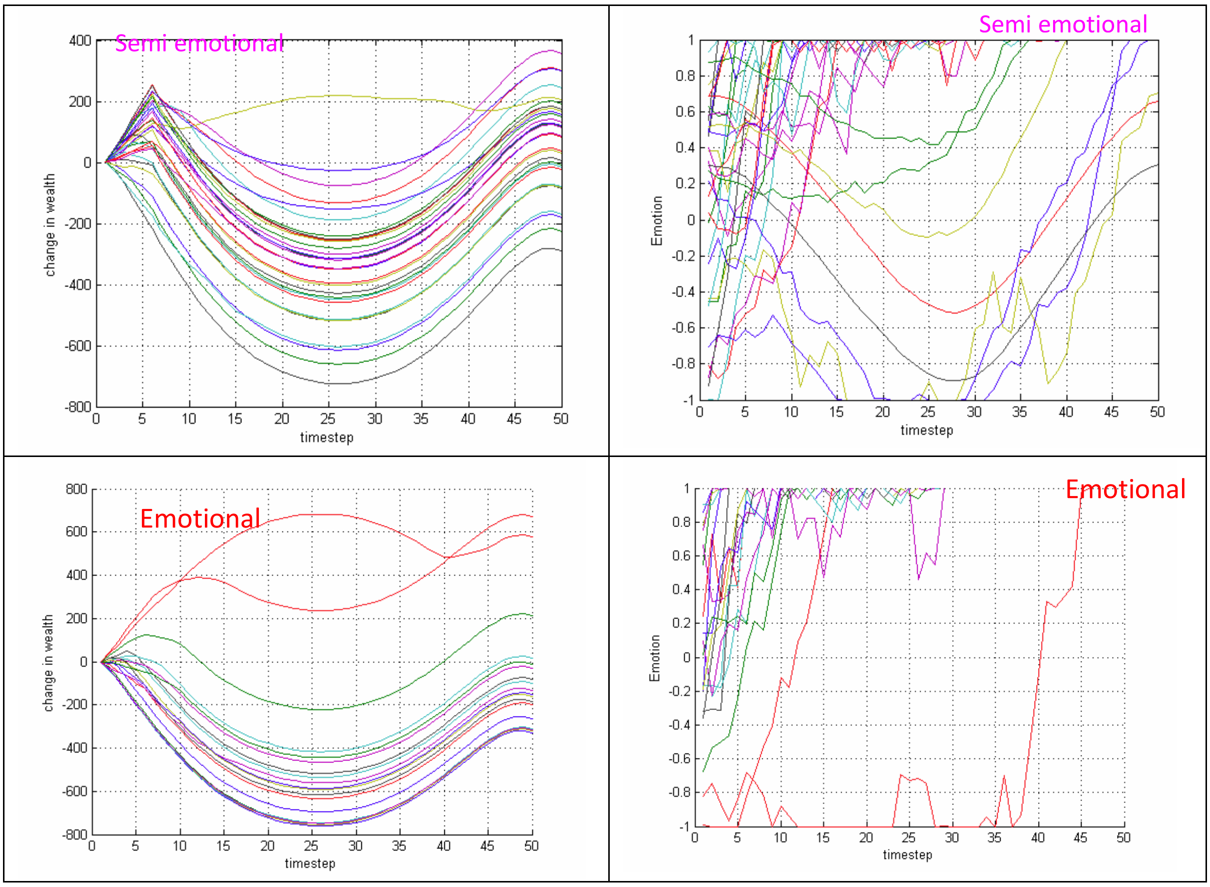


Figure (32) shows investors emotions and wealth changes for the u shape price path shown in figure (4) were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50 .

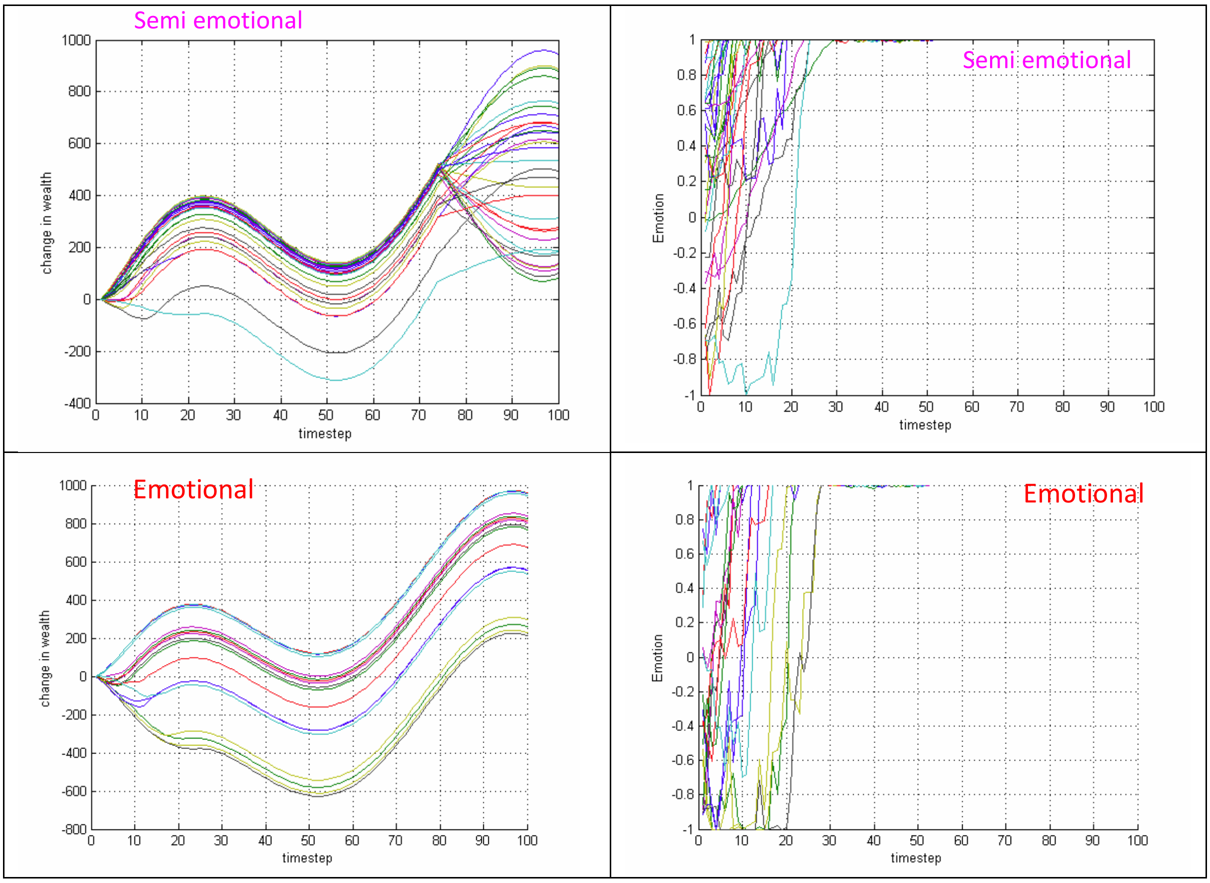


Figure (33) shows investors Emotions and wealth changes for the upward price path shown in figure (6) were the other Cascade parameters α , β and γ were fixed at 0.35 and $m_0=3$, N=50 .

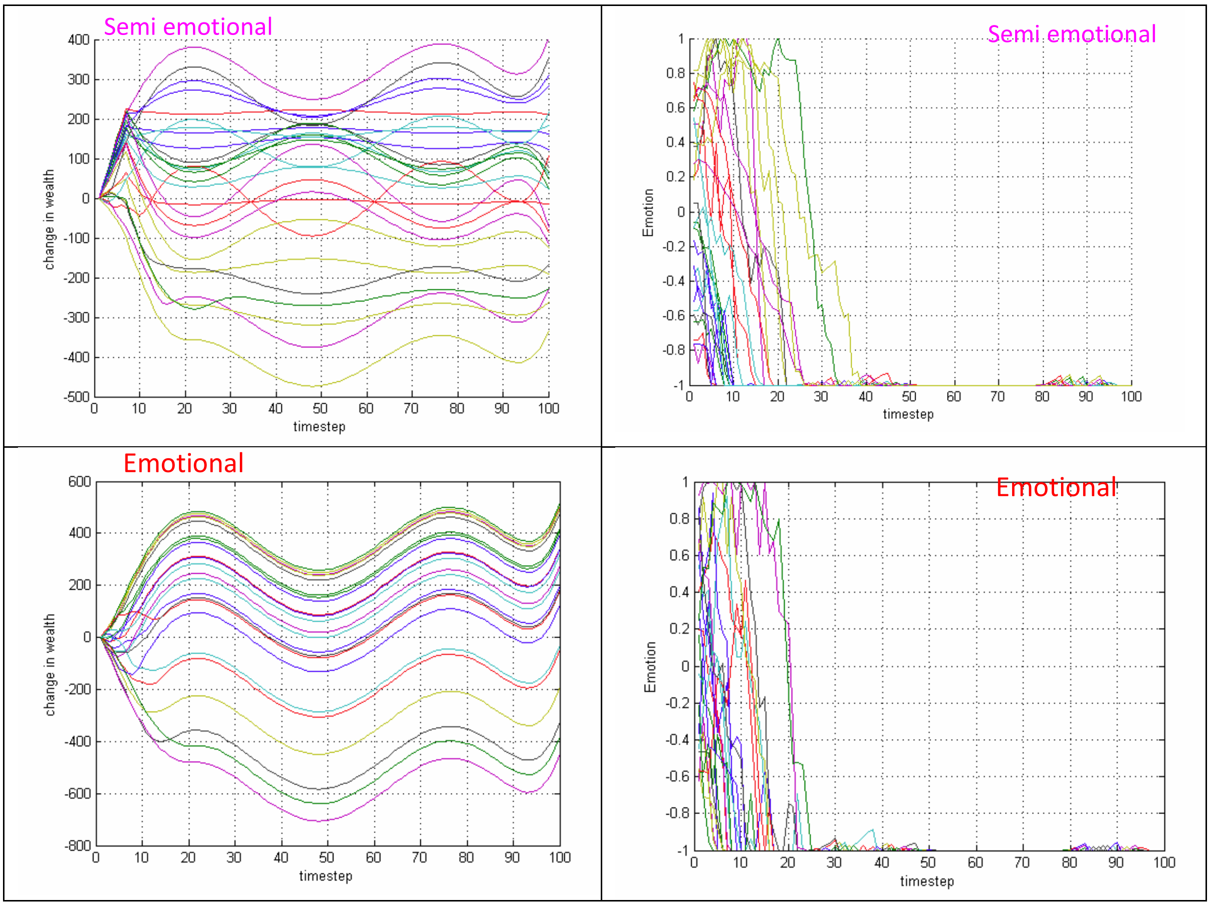
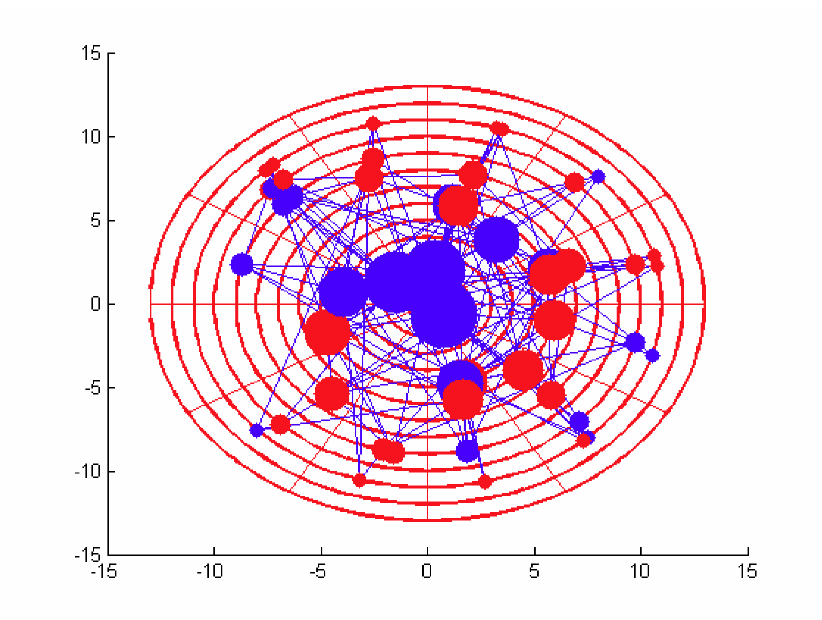


Figure (34) shows investors emotions and wealth changes for the downward price path shown in figure (8) were the other Cascade parameters α , β and γ were fixed at 0.35 and $m_0=3$, N=50 .

-Third for network with 50/50 emotional/rational investors.



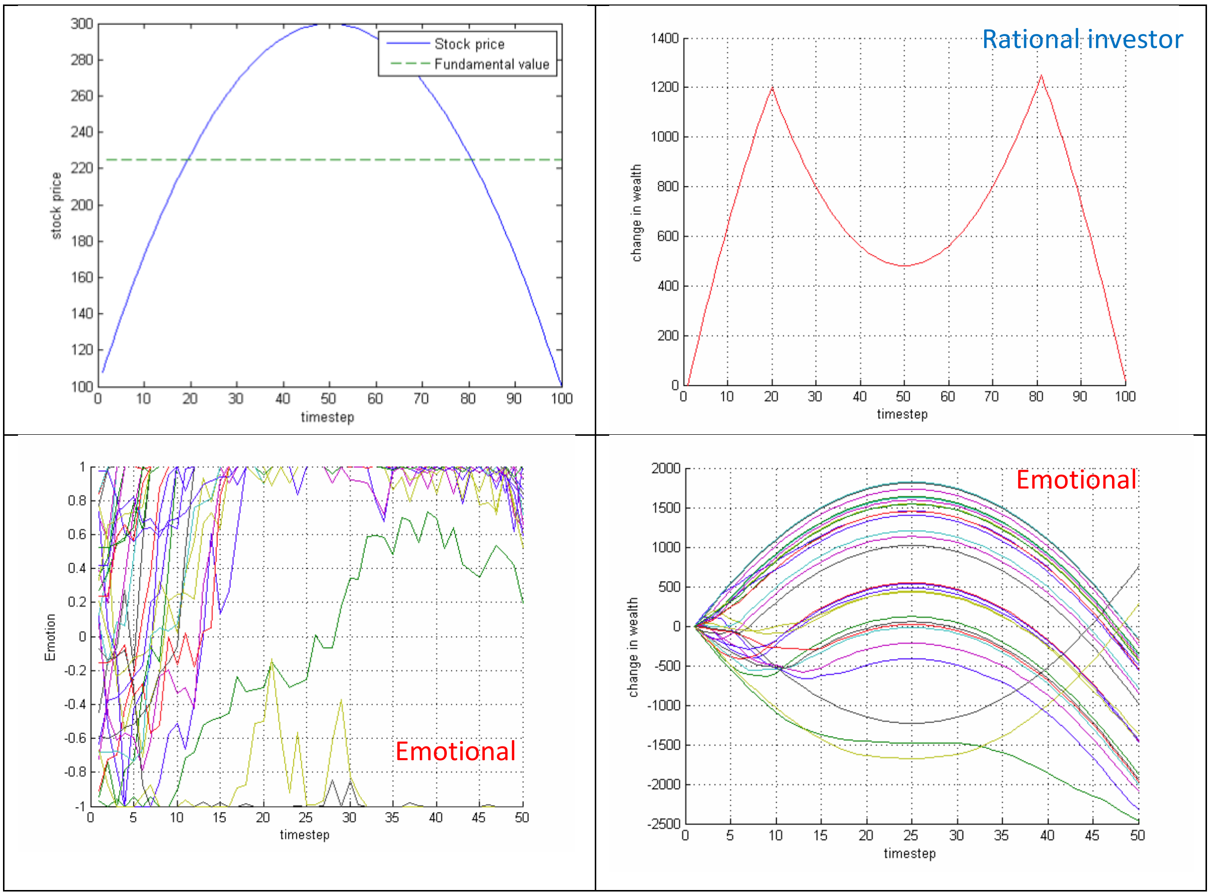


Figure (34) shows rational investor wealth changes for the n shape price path and emotional investor wealth and emotion change , were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50

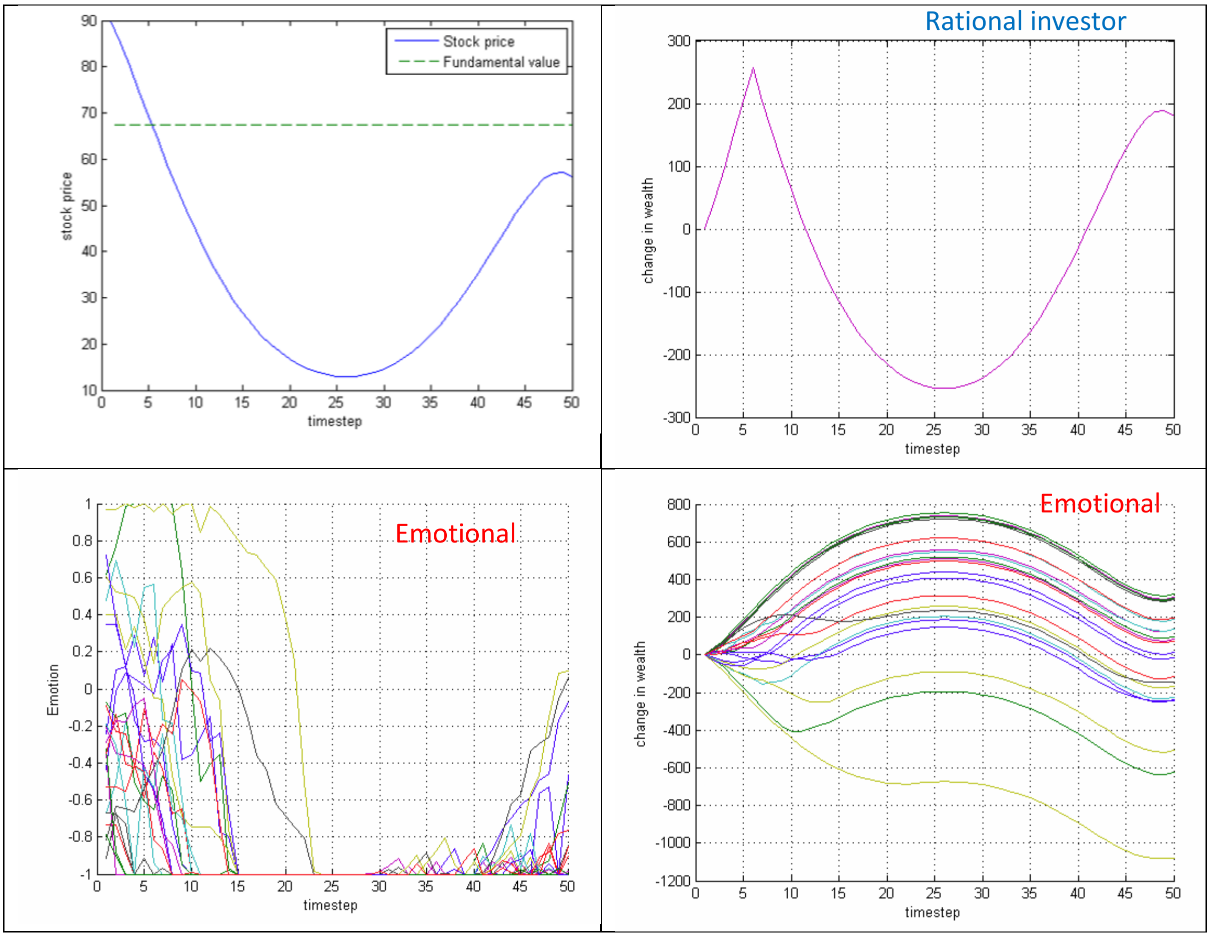


Figure (35) shows rational investor wealth changes for the u shape price path and emotional investor wealth and emotion change , were the other Cascade parameters α , β and γ were fixed at 0.35 and $m_0=3$, N=50 .

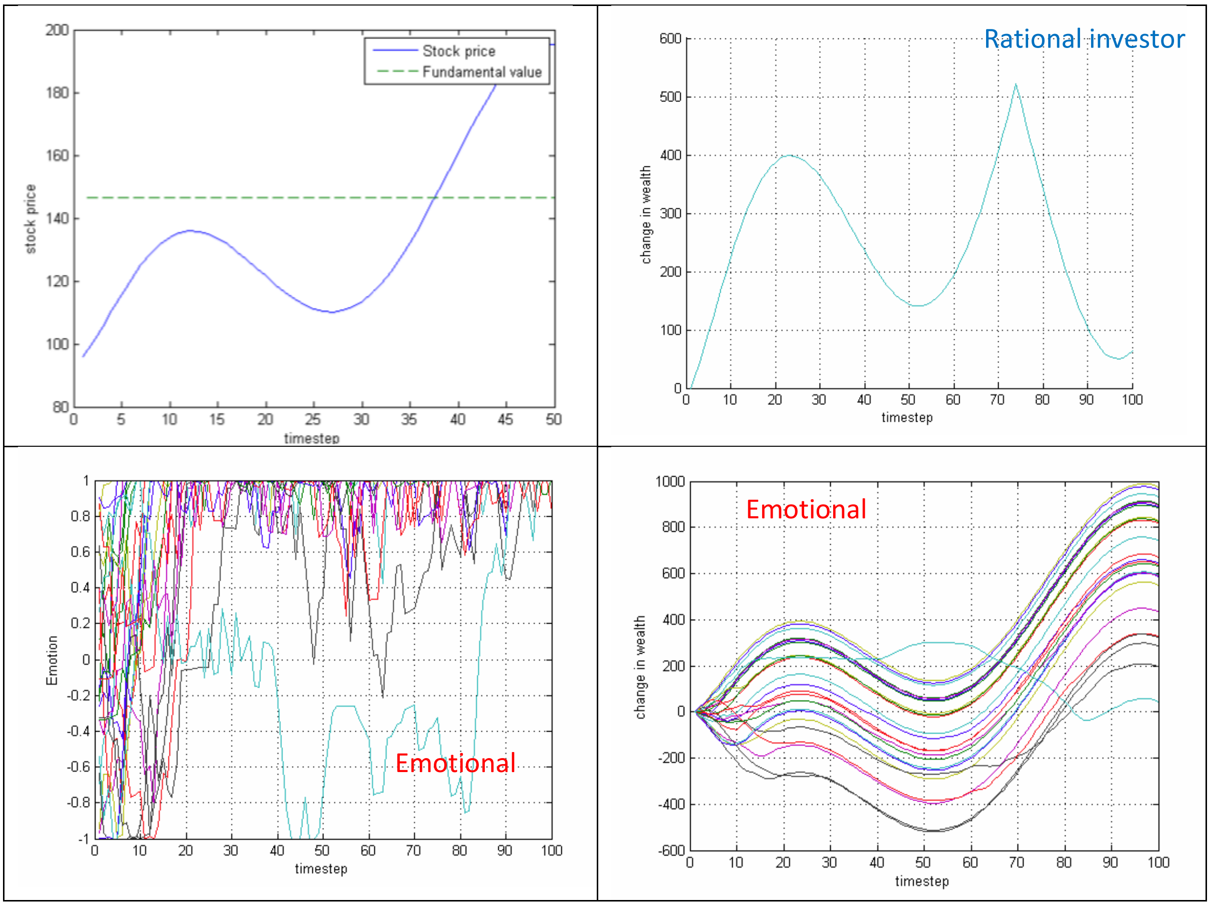


Figure (35) shows rational investor wealth changes for the upward price path and emotional investor wealth and emotion change , were the other Cascade parameters α , β and γ were fixed at 0.35 and $m_0=3$, N=50 .

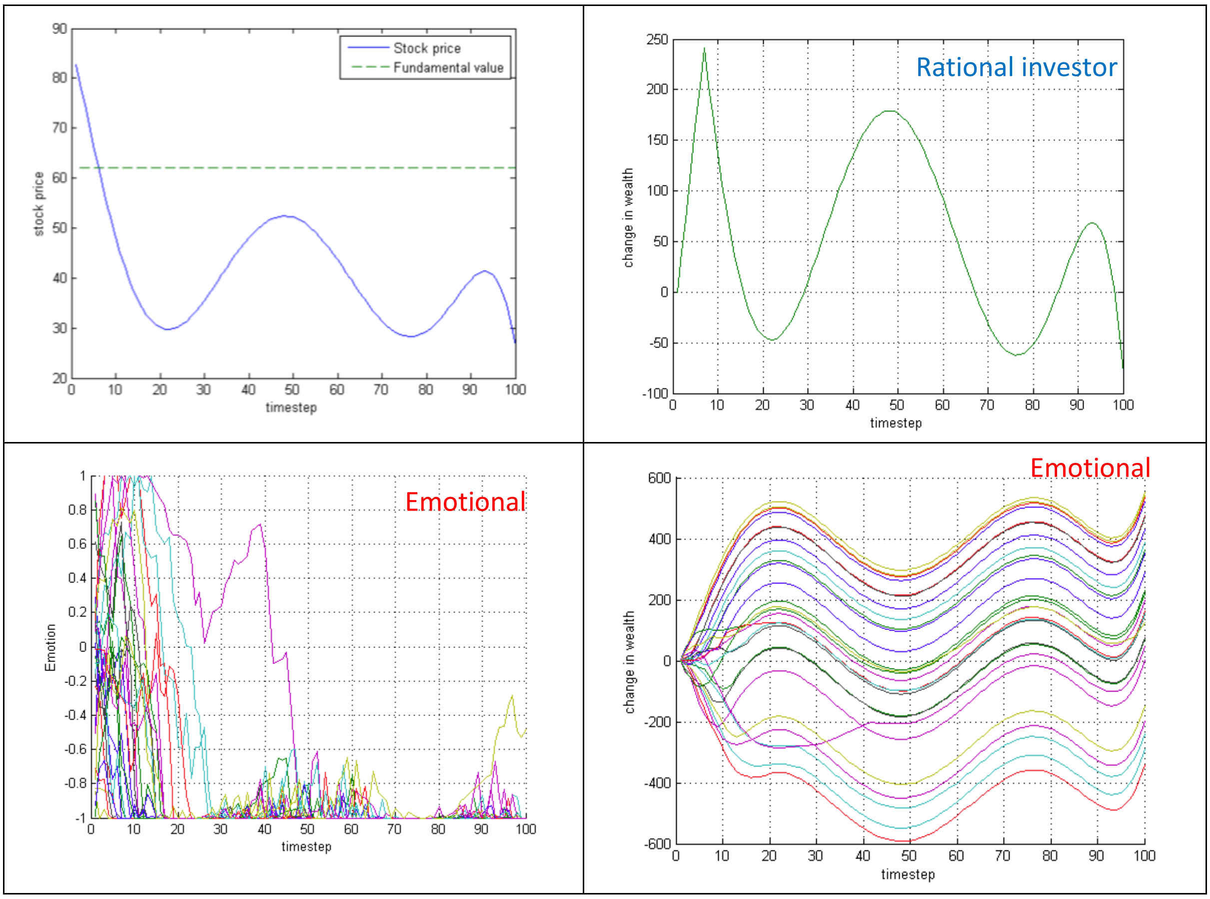


Figure (36) shows rational investor wealth changes for the downward price path and emotional investor wealth and emotion change , were the other Cascade parameters α , β and γ were fixed at 0.35 and m_0=3 , N=50 .

Appendix 2 Emotional Network Matlab code

Authors Mat lab code to generate the result presented
Note that the user have to download these supportive files from MIT Strategic Engineering Research Group website
http://strategic.mit.edu/downloads.php?page=matlab_networks

adj2adjL.m	BAalg.m	degrees.m
dijkstra.m	draw_circ_graph.m	eigencentrality.m
isconnected.m	newman_comm_fast.m	issymmetric.m
isdirected.m	kneighbors.m modularity_metric.m	subgraph.m
modularity_metric.m	newman_eigenvector_method.m	numedges.m
purge.m	node_betweenness_faster.m	random_graph.m
selfloops.m	sort_nodes_by_max_neighbor_degree.m	

```
%% Main script Run me
%% Housekeeping
clear all
close all
clc

%% Generate initial network
set(0,'DefaultFigureColormap',feval('jet'))

%%%% INPUTS %%%%
N=50;                   % Size of network
m0=3;                   % Minimum number of connections
noTimesteps=100;
beta = 0.05;             % Emotional price history factor
alpha = 0.5;            % emotional probability of affecting neighbour
gamma = 0.5;              % emotional propagation
%%%%%%%%%%%%%%%%

adj=BAalg(N,m0);        % Generate adjacency matrix using Barabasi-Albert alg

%% Assign Personalities
%%%% INPUTS %%%%
pRI=33/100;               % Percentage of Rational Investors
pII=33/100;               % Percentage of emotional Investors
pSI=1/10;                 % Percentage of Semi- emotional Investors
%%%%%%%%%%%%%%%%

% Create Network objects
for t=1:noTimesteps+1
    net(t)=Network(t, adj, pRI, pII);
end
for t=1:noTimesteps+1
    net(t).node=net(1).node;
end

%% Buy - Sell - Hold
% Call price path
  [pricePath fValue] = priceNvalue(noTimesteps);      % n shape Trend
% [pricePath fValue] = priceNvalue2(noTimesteps);     % u shape Trend
% [pricePath fValue] = priceNvalue3(noTimesteps);     % upward  Trend
% [pricePath fValue] = priceNvalue4(noTimesteps);       % downward Trend

for t=1:noTimesteps
```

```
    %Decide buy - sell - hold
    buySellFunc(net(t), pricePath, fValue, t, N)

    for i=1:N
        if t>1
            updateWealth(net(t), net(t-1), i, pricePath, fValue, t)
        end
    end


%% Update emotions
    updateEmotions(net,t,alpha,beta,gamma,pricePath)
end
%% Display Network
 figure(1)
 dot_matrix_plot(adj)
 figure(2)
 draw_circ_graph(adj)

%
 [y x]=hist(degrees(adj));
 figure(3)
 loglog(x,y)
 grid on


%% run for updating Herding and emotions
% pRewire=0.3;          % Rewiring probability

% for t=1:noTimesteps
    %% Decide buy - sell - hold
    % buySellFunc(net(t), pricePath, fValue, t, N)

   % for i=1:N
        % if t>1
           %  updateWealth(net(t), net(t-1), i, pricePath, fValue, t)
       %  end
    % end

    %% Update emotions
    % updateEmotions(net,t,alpha,beta,gamma,pricePath)
    % updateHerding(net,t,pRewire)
% end




%% Results
% store results

for t=1:noTimesteps
    for i=1:N
        E(t,i)=net(t).node(i).emotion;
        S(t,i)=net(t).node(i).settledWealth;
        k(t,i)=net(t).node(i).degree;
    end
end
```

```
%
% plot show the wealth of each group of investors
figure (4)
  for i=1:N
    if net(1).node(i).emotionality==0
        plot3([1:noTimesteps],k(:,i),S(:,i),'r')
    elseif net(1).node(i).emotionality==1
        plot3([1:noTimesteps],k(:,i),S(:,i),'b')
    else
        plot3([1:noTimesteps],k(:,i),S(:,i),'g')
    end
     hold all
  end
xlabel('timestep')
 ylabel('investor degree')
 zlabel('change in wealth')
 grid on




% plot price path and fundamental value
figure(5)
plot([1:noTimesteps],pricePath(1:end-1))
hold all
plot([1:noTimesteps],fValue(1:end-1),'LineStyle','--')
xlabel('timestep')
ylabel('stock price')
legend('Stock price','Fundamental value')


%% rational investor plot change in wealth and emotion
figure (6)
 for i=1:N
    if net(1).node(i).emotionality==0
        plot([1:noTimesteps],S(:,i))
    elseif net(1).node(i).emotionality==1
      %   plot3([1:noTimesteps],S(:,i),'b')
    else
      %  plot3([1:noTimesteps] ,k(:,i),S(:,i),'g')
    end
     hold all
 end
 xlabel('timestep')
 ylabel('change in wealth')
 grid on


 figure (7)
 for i=1:N
    if net(1).node(i).emotionality==0
        plot([1:noTimesteps],E(:,i))
    elseif net(1).node(i).emotionality==1
      %   plot3([1:noTimesteps],S(:,i),'b')
    else
      %  plot3([1:noTimesteps] ,k(:,i),S(:,i),'g')
    end
     hold all
 end
  xlabel('timestep')
```

```
  ylabel('Emotion')
 grid on

 %% semi-emotional investor plot change in wealth and emotion
 figure (8)
 for i=1:N
    if net(1).node(i).emotionality==0;
        % plot3([1:noTimesteps],k(:,i),S(:,i))
    elseif net(1).node(i).emotionality==1;
        % plot3([1:noTimesteps],S(:,i),'b')
    else  and (net(1).node(i).emotionality==1 ,
net(1).node(i).emotionality==0);
        plot([1:noTimesteps] ,S(:,i));
    end
     hold all
 end
 xlabel('timestep')
 %ylabel('investor degree')
 ylabel('change in wealth')
 grid on

 figure (9)
 for i=1:N
    if net(1).node(i).emotionality==0;
        % plot3([1:noTimesteps],k(:,i),S(:,i))
    elseif net(1).node(i).emotionality==1;
        % plot3([1:noTimesteps],S(:,i),'b')
    else  and (net(1).node(i).emotionality==1 ,
net(1).node(i).emotionality==0);
        plot([1:noTimesteps] ,E(:,i));
    end
     hold all
 end
  xlabel('timestep')
  ylabel('Emotion')
 grid on


%% emotional investor plot change in wealth and emotion

 figure (10)
 for i=1:N
    if net(1).node(i).emotionality==0
    elseif net(1).node(i).emotionality==1
       plot([1:noTimesteps],S(:,i))
        % plot([1:noTimesteps],S(:,i))
    else
    end
     hold all
 end
  xlabel('timestep')
 %ylabel('investor degree')
 ylabel('change in wealth')
 grid on

% 2d plot of emotional conversion
  figure (11)
 for i=1:N
    if net(1).node(i).emotionality==0
    elseif net(1).node(i).emotionality==1
```

```
        plot([1:noTimesteps],E(:,i))
    else
    end
     hold all
 end
  xlabel('timestep')
  ylabel('Emotion')
 grid on


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Modularity
  figure(12)
 [xy(:,1) xy(:,2), numGroups] = networkShellCoordinates(adj);

%  %% Create network
  figure(13)
  for i=1:max(sum(adj))
     viscircles([0, 0], i);
     hold on
  end

  for i=1:numGroups
           theta=(i-1)*2*pi/numGroups;
      temp(1,:)=[0 0];
     temp(2,:)=[max(sum(adj))*sin(theta),max(sum(adj))*cos(theta)];
      plot(temp(:,1),temp(:,2),'r-')
      hold on
  end
  gplot(adj, xy)
  hold on

  for i=1:N
     if net(1).node(i).emotionality==0
         plot(xy(i,1), xy(i,2),'.','MarkerSize', net(t).node(i).degree*8,
'MarkerEdgeColor', [0 0 1])
    elseif net(1).node(i).emotionality==1
         plot(xy(i,1), xy(i,2),'.','MarkerSize', net(t).node(i).degree*8,
'MarkerEdgeColor', [1 0 0])
     else
         plot(xy(i,1), xy(i,2),'.','MarkerSize', net(t).node(i).degree*8,
'MarkerEdgeColor', [1 0 1])
     end
  end
%   grid on

%% Function to visualize networks
% This function sorts an adjacency matrix into shells of degrees and
% assigns x y coordinates. The node positions angular position is sorted by
% modular groups.
% INPUTS = (adjacency matrix)
% OUTPUTS = x,y coordinates of the n nodes

function [x y, numGroups] = networkShellCoordinates(adj)



%% Extract data into useable arrays - degrees groups and shells
N=length(adj(1,:));      % Number of nodes
```

```
degrees=sum(adj);        % degrees of the nodes and modulus

[groups_hist,Q]=newman_comm_fast(adj);              % Use Newman's fast
community detection algorithm

groups=zeros(1,N);                                  % Assign group numbers
for i=1:length(groups_hist{1,find(Q==max(Q))})
    groups(groups_hist{1,find(Q==max(Q))}{i})=i;
end

%% Assign angles
for i=1:max(groups)
    ID=find(groups==i);
    for ii=1:length(ID)
        sectorAngle=2*pi/max(groups);
        angle1=sectorAngle*(i-1) + sectorAngle/3;
        angles(ID(ii))=angle1 + (sectorAngle/3)/length(ID)*(ii-1);
    end
    clear ID
end

%% Convert to cartesian
x=(max(degrees)-degrees+1) .* sin(angles);
y=(max(degrees)-degrees+1) .* cos(angles);

numGroups=max(groups);


 %% Simple test price path & fundamental value for the n shape trend
%%
function [pricePath fValue] = priceNvalue(noTimesteps)

x=1:noTimesteps+1;
initial=100;
peak=300;
pricePath=-((peak-initial)*4)/noTimesteps^2  .*  x.^2    +   ((peak-
initial)*4)/noTimesteps  .*  x   + 100;
fValue=ones(1,length(x)) * peak*0.75;

% Simple test price path & fundamental value for the u shape trend
function [pricePath fValue] = priceNvalue2(noTimesteps)

x=1:noTimesteps+1;
y=1:(11/max(x)):11+ (((noTimesteps/10)-1)*(11/max(x)) );
pricePath=  -0.00186 *y.^6 +  0.06656 *y.^5 -0.941  *y.^4 + 6.604  *y.^3
...
-20.96 * y.^2  + 5.016 *y  + 100;
fValue=ones(1,length(y)) * max(pricePath)*0.75;

% Simple test price path & fundamental value for the upper shape trend
function [pricePath fValue] = priceNvalue3(noTimesteps)
x=1:noTimesteps+1;
y=1:(11/max(x)):11+ (((noTimesteps/10)-1)*(11/max(x)) );
pricePath=  0.003429*y.^6 - 0.1471 *y.^5 + 2.319 *y.^4 -16.259*y.^3 +...
48.057 * y.^2    - 37.933 *y  + 100;
fValue=ones(1,length(y)) * max(pricePath)*0.75;
```

```
% Simple test price path & fundamental value for the downward shape trend
function [pricePath fValue] = priceNvalue4(noTimesteps)

x=1:noTimesteps+1;
y=1:(11/max(x)):11+ (((noTimesteps/10)-1)*(11/max(x)) );
% y=1:(10/max(x)):10+(10/max(x))+ (10/max(x));
pricePath=  -0.007687*y.^6   + 0.2752 *y.^5   -3.6609  *y.^4 +21.81 * y.^3
+...
 -52.73 * y.^2    + ....
17.14  *y  + 100;
fValue=ones(1,length(y)) * max(pricePath)*0.75;




%% Node Objects
classdef Network < handle
    %% Define Node properties
    properties
        time;
        adj;
        node;
%          degree;
%          emotionality;
%          emotion;
%          interimWealth;
%          settledWealth;
%          stock;
%
    end

    %% Define Methods and functions for Node class
    methods
        %% Define obj.ID where ID is the name
        function obj = Network(t, adj, pRI,pII)
            obj.time = t;                              %Just the name
            obj.adj= adj;
            for i=1:length(adj(1,:))
                obj.node(i).degree=sum(adj(i,:));
                obj.node(i).emotion=rand*2-1;
                obj.node(i).interimWealth = 0;
                obj.node(i).settledWealth = 0;
                obj.node(i).stock = 0;
                a=rand;
                if a<pRI
                    obj.node(i).emotionality=0;
                elseif a<pII+pRI
                    obj.node(i).emotionality=1;
                else
                    obj.node(i).emotionality=rand();
                end

          obj.node(i).fri = floor(abs(random(makedist('Normal'))))*20;
            end
        end


        %% Choose buy or sell
        function buySellFunc(obj, pricePath, fValue, t, N)
```

```
            for i=1:N
obj.node(i).stock = sign(fValue(t)-pricePath(t)) * (1-
obj.node(i).emotionality) * 10 +...
 (obj.node(i).emotion) * (obj.node(i).emotionality)* obj.node(i).fri;

                obj.node(i).interimWealth = -obj.node(i).stock *
pricePath(t);
            end
        end

        function updateWealth(obj, objOld, i, pricePath, fValue, t)
            obj.node(i).settledWealth = objOld.node(i).settledWealth +
objOld.node(i).stock * pricePath(t)...
                + objOld.node(i).interimWealth;
        end

 %% Update emotions
        function updateEmotions(obj,t,alpha,beta,gamma,pricePath)
            N=length(obj(t).node);
            meanPrice=mean(mean(pricePath( ((t-5)*((t-5)>0))+1:t)));    %
Set mean price over last five points
            for i=1:N
                neighboursID=find(obj(t).adj(i,:)>0);
%Node(i) neighbours ID
                obj(t+1).node(i).emotion = obj(t).node(i).emotion +
beta*(pricePath(t)-meanPrice)/meanPrice;       % update Node(i) emotion
based on price difference
                for ii=1:length(neighboursID)
% update Node(i) emotion based on each neighbours (ii)'s emotions

                    if alpha>rand
                        obj(t+1).node(i).emotion = obj(t+1).node(i).emotion
+ obj(t).node(i).emotionality*gamma*obj(t).node(neighboursID(ii)).emotion;
                    end

                end

                if abs(obj(t+1).node(i).emotion)>1
                   obj(t+1).node(i).emotion =
sign(obj(t+1).node(i).emotion);
                end
            end
        end


 %% Update herding
        function updateHerding(obj,t,pRewire)
            obj(t+1).adj = obj(t).adj;

            for i = 1 : length(obj(t).node)
                wealth(i) = obj(t).node(i).settledWealth;
                obj(t).node(i).degree = sum(obj(t).adj(i,:));
            end
            if max(wealth) > 0
                wealth = wealth ./ max(wealth);
            else
                wealth = ones(1,length(wealth));
            end
```

```
            for i = 1 : length(obj(t).node)
                wealth(i) = wealth(i)*rand;
            end

            [sortedWealth ID] = sort(wealth, 'descend');

            sum(sum(obj(t).adj))
            for i = 1: length(obj(t).adj)
                for ii = i+1: length(obj(t).adj)
                    temp = obj(t).adj + obj(t+1).adj;
                    if obj(t).adj(i,ii)>0 & pRewire > rand & sum(temp(i,:)
== 0) >= 2
                        obj(t+1).adj(i,ii)=0;
                        obj(t+1).adj(ii,i)=0;
                        for iii = 1:length(ID)
                            if temp(i,ID(iii)) == 0 & (i == ID(iii)) == 0
                                obj(t+1).adj(i,ID(iii)) = 1;
                                obj(t+1).adj(ID(iii),i) = 1;
                                break
                            end
                        end
                    end
                end
            end
        end
    end
end


%% updating Herding and emotions




for t=1:noTimesteps
    %Decide buy - sell - hold
    buySellFunc(net(t), pricePath, fValue, t, N)

    for i=1:N
        if t>1
            updateWealth(net(t), net(t-1), i, pricePath, fValue, t)
        end
    end

    %% Update emotions
    updateEmotions(net,t,alpha,beta,gamma,pricePath)
    updateHerding(net,t,pRewire)
end
```

Herding Visulisation

```
function visualizeSmallNetwork( adj,nodeEMO )
if sum(sum(adj))>0
    %% Assign markersize based on eigenvector centrality
    eigCentrality = eigencentrality(adj);
    markerSize = (eigCentrality - min(eigCentrality)+1/100) * 100;
    %% Assign colour based on degree centrality
    degree=degrees(adj);
    % markerColormap=jet(length(adj));
    for i= 1:length(adj)
        if nodeEMO(i)==1
       markerColormap(i,: ) = [1 0 0];
        elseif nodeEMO(i)==0
     markerColormap(i,: ) = [0 0 1];
        else
       markerColormap(i,: ) = [1 0 1];
        end
    end

    %% Assign XY on the basis that networks change
    for i=1:length(adj)
        xy(1,i) = sin((i-1)*2*pi/length(adj));
        xy(2,i) = cos((i-1)*2*pi/length(adj));
    end

     %% Create network
    figure
    for i=1:length(adj)

plot(xy(1,i),xy(2,i),'bo','MarkerSize',markerSize(i),'MarkerFaceColor',markerColorm
ap(i,:))
        hold on
    end

    for i=1:length(adj)
        for j=1:length(adj)
            if adj(i,j)>0
                p1=xy(1:2,i);
                p2=xy(1:2,j);
                dp=p2-p1;
                quiver(p1(1),p1(2),dp(1),dp(2),0,'k-
','LineWidth',2*(adj(i,j))/(max(max(adj)))+1)
                hold on
            end
        end
    end
end
axis off
```

Appendix 3 : Experimental Method

For this study, we recruited 30 participants (18 male) with a mean age of 27.13 (S.D. 7.66). Most participants were students at the University of Anon. however a small sample of participants were University employees. Preliminary analyses revealed no systematic differences between student and non-student responses, and they have been combined in all analyses.

Participants received £5 remuneration for their participation. They were also told that they had a chance of winning a prize of up to £70 if their performance was in the top 10. We obtained informed written consent from all participants. Participants were tested in accordance with national and international norms governing the use of human research participants. The study was approved by the ethics committee of the University of Anon.

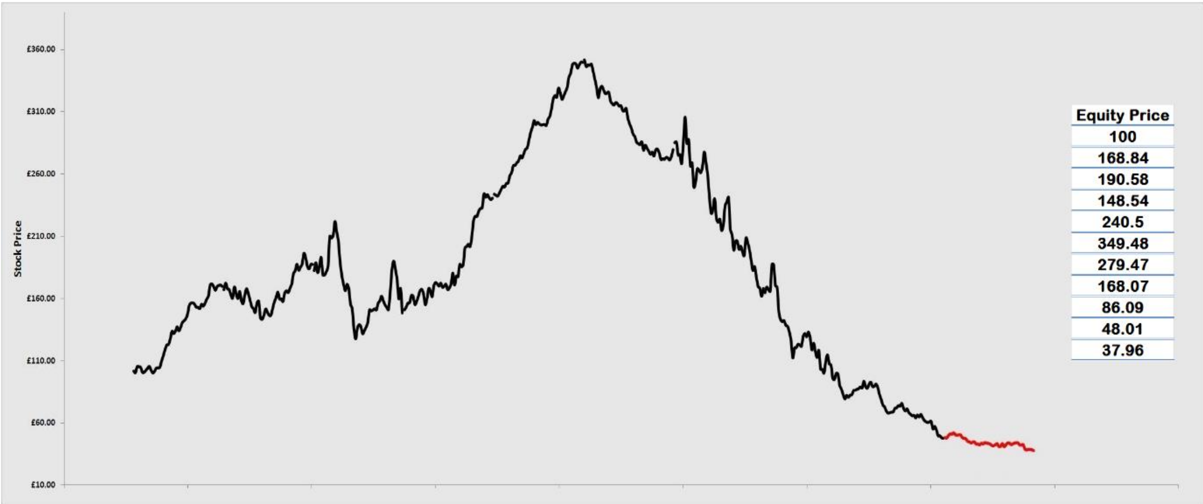
The materials required for the experiment comprised of a Positive and Negative Affect Schedule (PANAS), four Stock Market Simulation Tasks (SMST), and a financial risk profiling questionnaire. For the physiological data an electrocardiogram (ECG) and a Galvanic Skin Conductance (GSR) monitor was used. SMI eye tracking glasses recorded eye gaze. Finally a computer audio-recorder was used for the qualitative questions.

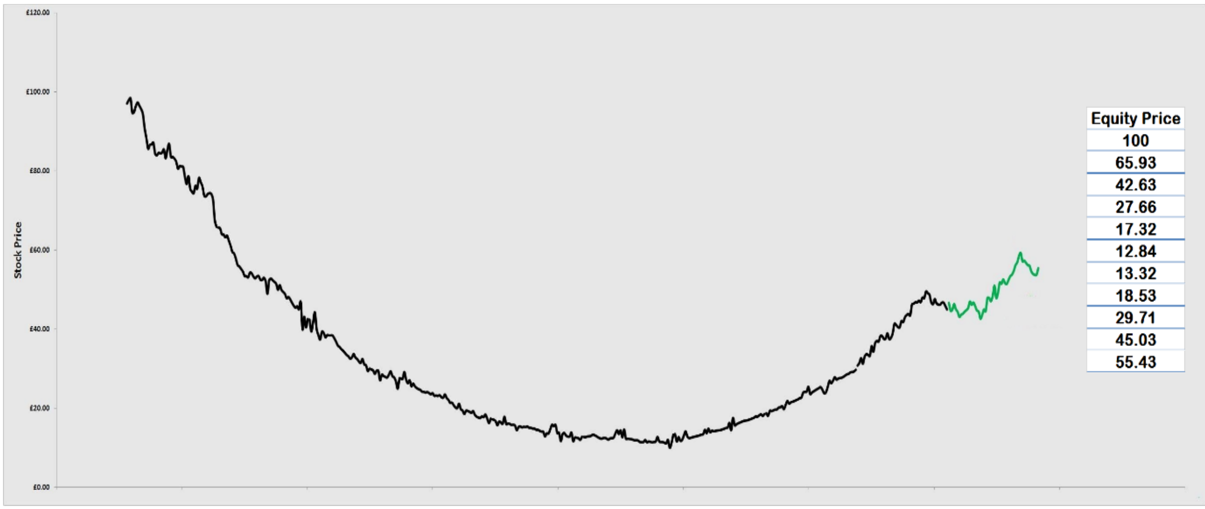
The pen and paper PANAS questionnaire assessed the participant's subjective experience at a given time (Watson et al. 1988). Participants appraised the 20-item self-report measure rating the extent to which they feel a particular emotion on a five-point scale (1="not at all" to 5="strongly").

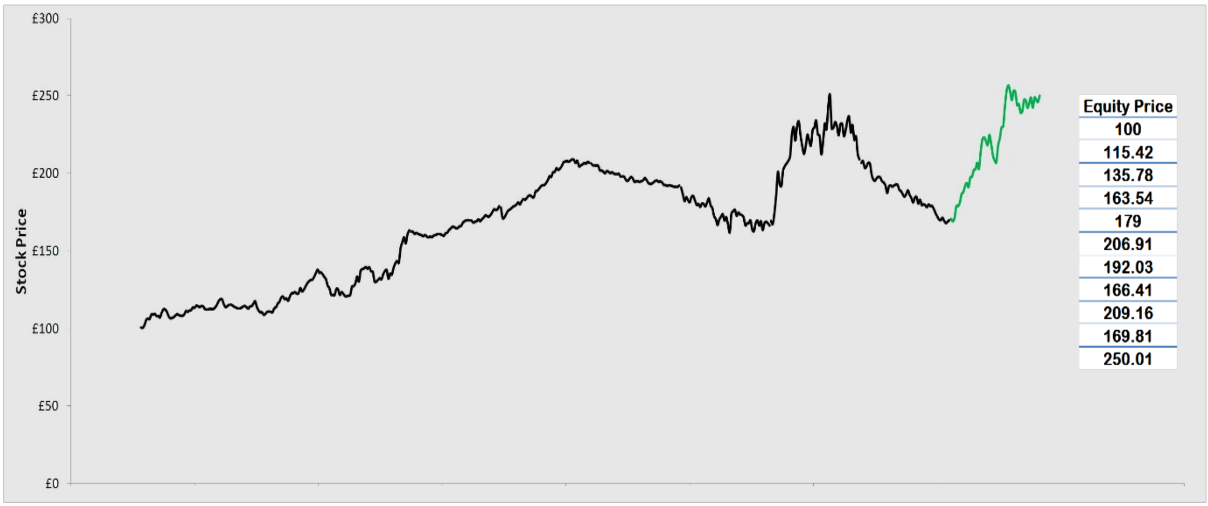
Participants were presented with four separate computerised Stock Market Simulation Tasks (SMST): they played each one in turn (the order of the SMST's was randomised, so that different participant may have played them in a different order). In each simulation task, participants were provided with 10 time points at which to make investment decisions (trading into or out of cash and stocks). At each time point, they would make their buying/selling decision, and then click the mouse, upon which the next segment of the stock-price time path would emerge.

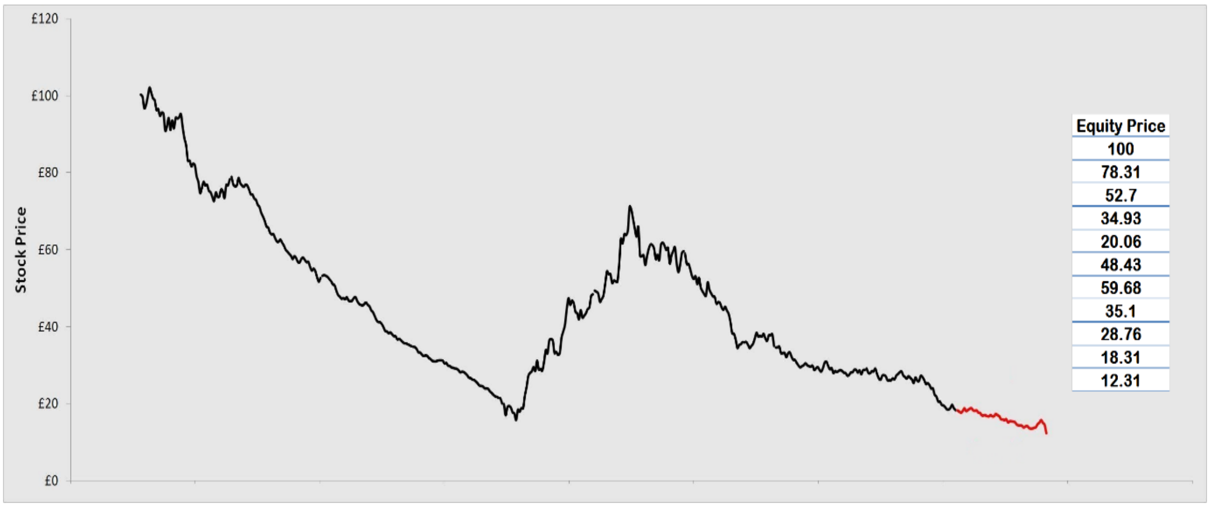
They were initially given 100 units in cash and £1000 in cash. They were informed that they would earn a risk-free 2% interest per period on any cash held, and that they would earn or lose money on the stock dependent on its current price. Participants were to invest in the stock simply by buying or selling stock units. Visual and descriptive information as to the behaviour of the stock and the amount of money they made in stocks, cash and overall was provided for each trial.

The four SMST only differed in the stock market fluctuation according to a particular stock market scenario. SMST 1 followed an “inverted U” stock market fluctuation, SMST 2 an “U” stock market scenario, SMST 3 an “upward” fluctuation and SMST 4 a “range trading” scenario. We note that the four time paths together represent an overall bear-market.









During the SMSTs, the electrocardiogram (ECG), the Skin Conductance Level (SCL) as well as eye gaze were constantly recorded.

The ECG was recorded from three Ag-AgCl lead electrodes. Skin conductance activity was measured using a constant voltage (0.5V) with an Ag-AgCl electrodes attached to the medial phalanx of the middle and index finger of the non-dominant hand. The eye gaze was recorded using SMI eye tracking glasses.

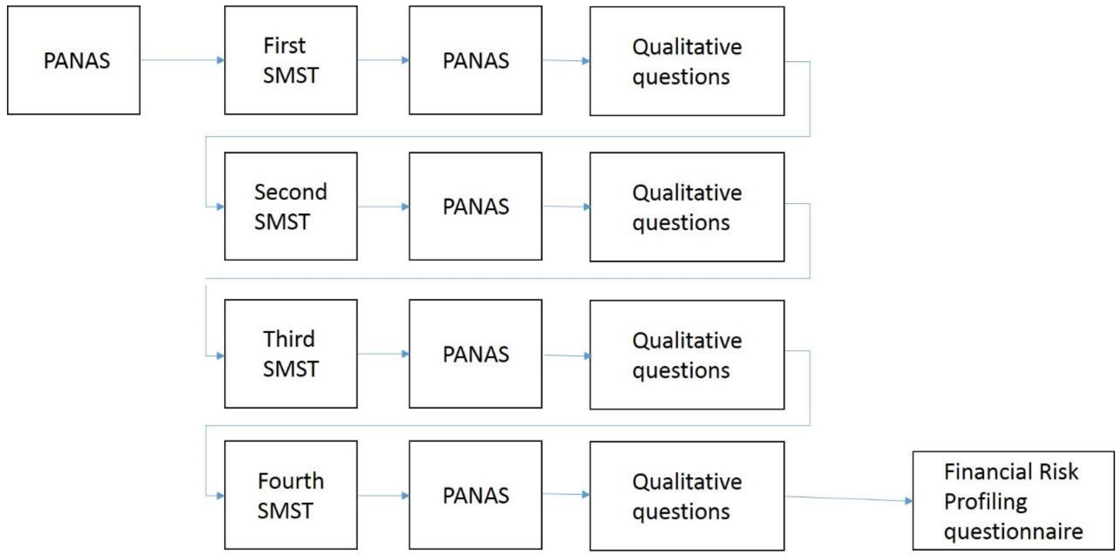
Participants were also given a computer based financial risk profiling questionnaire (available on request from the authors) based on prospect theory, assessing participant's risk and loss profiles. The questionnaire comprised of an initial question requiring the participant to state his/her total investment in financial markets, followed by six hypothetical investment scenarios in which they were to choose between a risky and sure option, for three of the investment scenarios, participants were asked to detail at which percentage level they were willing to choose the risky option. Finally the participants were asked to briefly explain why they invested in financial markets.

Each participant first read the briefing sheet, gave written consent to participate and were allocated a participant number. They answered the demographic questionnaire providing information pertaining to their age, sex, gender, ethnicity, their educational level, their University department and if they had already invested in stock markets (if so for how long and how regularly).

Participants first answered a Positive and Negative Affect Schedule (PANAS) questionnaire so as to establish an emotional baseline. They were then equipped with skin conductance and heart rate monitors as well as eye tracking glasses. Participants then started their first SMST. All four SMST were counterbalanced for each participant. For the SMST, participants were instructed that they had inherited £20,000, half in stocks and half in cash. Over a 10 year period, they were to decide the amount they wished to invest in stock and the amount they would like to save as cash. The participant were told that their goal was to make as much money overall as they possibly could and were reminded of the prize incentive.

After each SMST participants were to answer a PANAS questionnaire. It was emphasised that the participant should answer the questionnaire relative to “how he is feeling at this moment in time”. Participants then answered two qualitative questions: -“Why did you perform in the way you did?” and “Can you tell me how you felt throughout the task?” Once the participant had finished all four SMST, the financial risk profiling questionnaire was provided.

Figure 2. Flow diagram of the experimental procedure



Participants were then verbally debriefed and thanked for their involvement in the experiment.

Appendix 4: Calculation of CRRA from questionnaire

1.1. Calculation of CRRA, CRRS, and loss aversion

From our questionnaire, we were able to calculate CRRA (question X), CRRS (question Y), and loss aversion as follows.

Following standard methodology, we employed the CRRA function:

From question X, we obtain the following. The question offers a choice of two gambles: £300 for sure, or a 50/50 gamble with a downside of £100. The subject was asked the minimum level of the upside to accept the risky gamble. Say the subject rejects the risky gamble up to and including 700, but accepts it for 750 onwards. Then we can calculate the CRRA as in the following Table appendix 4.1:

P success Gamble	C sure	C high	C low	CRRA = A	1 –A
0.5	300	500	100	0.7	0.3
0.5	300	550	100	0.7	0.3
0.5	300	600	100	0.7	0.3
0.5	300	650	100	0.7	0.3
0.5	300	700	100	0.7	0.3
0.5	300	750	100	0.7	0.3
0.5	300	800	100	0.7	0.3
0.5	300	850	100	0.7	0.3
0.5	300	900	100	0.7	0.3
0.5	300	950	100	0.7	0.3
0.5	300	1000	100	0.7	0.3

Table appendix 4.1 calculate the constant relative risk aversion

C high	Utility Safe		Utility gamble Success	Failure	Expected utility
500	18.45		21.51	13.27	17.39
550	18.45		22.13	13.27	17.70
600	18.45		22.72	13.27	17.99
650	18.45		23.27	13.27	18.27
700	18.45		23.79	13.27	18.53
750	18.45		24.29	13.27	18.78
800	18.45		24.76	13.27	19.02
850	18.45		25.22	13.27	19.24
900	18.45		25.65	13.27	19.46
950	18.45		26.07	13.27	19.67
1000	18.45		26.48	13.27	19.87

Table appendix 4.2 shows the calculation of the expected utility

Therefore, for this subject, CRRA = 0.7, where utility of safe equals expected utility of gamble. We repeat in the negative domain to estimate CRRS.

Questions enables us to obtain coefficient of loss aversion. Combining CRRA, CRRS and loss aversion, we obtain an individual's prospect theory diagram: as in the following example:

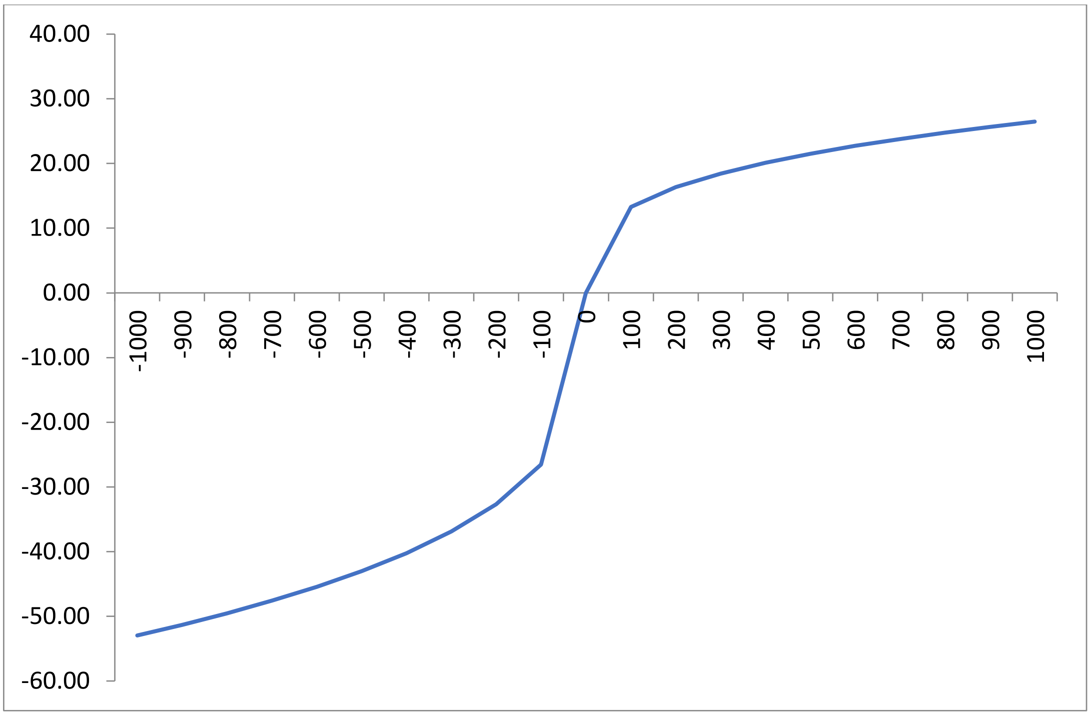


Figure shows the prospect theory curve where x-axis shows the gain and gain , y axis represent Utility cost

Prospect theory With loss aversion	
Wealth	Utility
-1000	-52.96
-900	-51.31
-800	-49.53
-700	-47.58
-600	-45.43
-500	-43.01
-400	-40.23
-300	-36.90
-200	-32.68
-100	-26.54
0	0.00
100	13.27
200	16.34
300	18.45
400	20.11
500	21.51
600	22.72
700	23.79
800	24.76
900	25.65
1000	26.48

Table appendix 4.3 shows the calculation of the utility from the wealth gain or loss.

Appendix 5: Perfect Trader's Strategy and Performance

A perfect trader (with a crystal ball!) would buy to the maximum immediately before a price rise, and sell to the maximum immediately before a price fall. In doing so, he would achieve the following returns and volatility of wealth.

Perfect Trader's Returns

	Game 1	Game 2	Game 3	Game 4	Overall
Returns	30.32%	-17.48%	8.35%	-10.36%	
	12.09%	1.98%	16.22%	1.98%	
	1.98%	1.98%	18.58%	1.98%	
	48.03%	1.98%	9.02%	1.98%	
	37.29%	1.98%	14.47%	88.09%	
	1.98%	3.67%	1.98%	20.88%	
	1.98%	33.00%	1.98%	1.98%	
	1.98%	47.20%	22.83%	1.98%	
	1.98%	37.03%	1.98%	1.98%	
	1.98%	25.32%	38.60%	1.98%	
Average	13.96%	13.67%	13.40%	11.25%	13.07%
Volatility	17.76%	20.54%	11.53%	28.02%	19.46%

Table appendix 5.1 shows game by game calculation of the returns and volatility for the four price paths

Appendix 6: CRRA, GSR and trading performance by Participant

Participant	GSR	CRRA	E utility	With emotions	Average % Per-period Returns		Volatility %	Sharpe Ratio	Total % Returns over whole game
1	0.19	0.99	-0.01	-0.01	0.41		12.74	-0.03	15.86
2	0.14	0.85	-0.09	-0.1	-3.67		24.68	-0.08	-73.93
3	0.17	0.26	-0.04	-0.05	-2.2		26.89	-0.05	-55.14
4	0.09	0.68	-0.02	-0.02	0.03		15.67	-0.05	1.13
5	0.03	0.68	0.03	0.03	3.81		11.37	0.08	284.15
6	0.08	0.03	0	0	-0.17		10.68	-0.05	-5.93
7	0.14	0.58	0.03	0.02	3.58		13.51	0.13	254.80
8	0.02	0.85	-0.06	-0.06	-2.1		21.54	-0.08	-53.40
10	0.38	0.38	0.02	0.01	2.31		13.1	0.01	127.92
11	0.1	0.85	-0.1	-0.11	-2.57		29.07	-0.07	-60.78
12	0.19	0.99	-0.12	-0.14	-3.61		29.93	-0.09	-73.39
13	0.02	0.7	-0.02	-0.02	0.01		16.2	-0.04	0.47
14	0.04	0.49	-0.01	-0.02	0.59		20.51	-0.03	23.61
15	0.06	0.85	0.02	0.02	2.51		6.74	0.05	143.91
16	0.1	0.77	-0.02	-0.02	-0.13		16.31	-0.07	-4.72
17	0.18	0.68	0.01	0.01	2.01		11.68	0.00	104.69
18	0.03	0.68	0.04	0.04	4.31		10.37	0.10	357.07
19	0.04	0.68	0	0	1.28		11.2	-0.03	58.21
20	0.05	0.49	0	0	0.69		14.89	-0.04	27.96
21	0.04	0.85	-0.05	-0.05	-1.97		17.8	-0.11	-51.15
22	0.03	0.93	-0.05	-0.05	-1.97		18.92	-0.07	-51.20
23	0.15	0.58	0.01	0.01	1.88		8.24	-0.01	95.65
24	0.03	0.58	-0.07	-0.07	-3.33		24.32	-0.08	-70.46
25	0.09	0.85	-0.02	-0.03	0.42		17.98	-0.03	16.41
26	0.12	0.49	0	-0.01	0.68		14.05	-0.05	27.80
27	0.09	0.68	-0.02	-0.03	-0.24		17.35	-0.04	-8.26
28	0.11	0.99	0.01	0	2.06		12.41	0.00	108.63
29	0.13	1	-0.1	-0.11	-3.24		26.65	-0.08	-69.46
30	0.21	0.68	0.01	0.01	1.9		11.77	0.00	96.89

Table appendix 6.1 shows each trader return over the four games.

This table presents a detailed numerical analysis of traders' CRRA, GSR and trading performance. From this table, we can calculate average performance across all of the traders, as follows:

Average Trader Return per period = 0.11% (which equates to an overall average return over all traders over 36 periods of a meagre 4%)

Average Trader Volatility = 16.78%

Average Sharpe Ratio = -0.08

Appendix 7: Performance from passively sitting in shares for the whole game

Trend 1:

	unit Stock Value	total Wealth	**Exp Return**
	100	20000	
end year 1	168.84	27084.00	30.32%
end year 2	190.58	30563.79	12.09%
end year 3	148.54	23838.81	-24.85%
end year 4	240.5	38553.86	48.07%
end year 5	349.48	55992.14	37.32%
end year 6	279.47	44792.04	-22.32%
end year 7	168.07	26969.58	-50.73%
end year 8	86.09	13854.35	-66.61%
end year 9	48.01	7763.15	-57.92%
end year 10	37.96	6156.78	-23.18%
		Average return	-11.78%
		Volatility	41.37%

Table appendix 7.1 shows for trend 1 the returns and Volatility for passive trader.

Trend 2

	unit Stock Value	total Wealth	**Exp Return**
	100	20000	
end year 1	65.93	16793.00	-17.48%
end year 2	42.63	10875.74	-43.44%
end year 3	27.66	7074.31	-43.01%
end year 4	17.32	4448.92	-46.38%
end year 5	12.84	3312.00	-29.51%
end year 6	13.32	3434.93	3.64%
end year 7	18.53	4759.30	32.61%
end year 8	29.71	7600.08	46.81%
end year 9	43.03	10984.43	36.83%
end year 10	55.43	14135.13	25.22%
		Average return	-3.47%
		Volatility	36.82%

Table appendix 7.2 shows for trend 2 the returns and Volatility for passive trader.

Trend 3

	unit Stock Value	total Wealth	Exp Return
	100	20000	
end year 1	115.42	21742.00	8.35%
end year 2	135.78	25570.54	16.22%
end year 3	163.54	30790.30	18.58%
end year 4	179	33697.67	9.02%
end year 5	206.91	38945.67	14.47%
end year 6	192.03	36149.16	-7.45%
end year 7	166.41	31333.55	-14.30%
end year 8	209.16	39371.52	22.84%
end year 9	169.81	31974.71	-20.81%
end year 10	250.01	47053.32	38.63%
		Average return	8.56%
		Volatility	18.09%

Table appendix 7.3 shows for trend 3 the returns and Volatility for passive trader.

Trend 4

	unit Stock Value	total Wealth	EXP Return
	100	20000	
end year 1	78.31	18031.00	-10.36%
end year 2	52.7	9927.69	-59.68%
end year 3	34.93	8054.40	-20.91%
end year 4	20.06	4634.71	-55.26%
end year 5	48.43	11160.22	87.88%
end year 6	59.68	13748.15	20.85%
end year 7	35.1	8095.19	-52.96%
end year 8	28.76	6637.43	-19.85%
end year 9	18.31	4234.38	-44.95%
end year 10	12.31	2854.84	-39.42%
		Average return	-19.47%
		Volatility	45.09%

Table appendix 7.4 shows for trend 4 the returns and Volatility for passive trader.

Whole game (trends 1-4 aggregated)

	Average return	Volatility
Trend 1	-11.78%	41.37%
Trend 2	-3.47%	36.82%
Trend 3	8.56%	18.09%
Trend 4	-19.47%	45.09%
Average	**-6.54%**	**35.34%**

Table appendix 7.5 shows summary table for returns and Volatility for passive trader over the 4 trends.

Appendix 8: PANAS (Positive and negative affect schedule) questionnaires

This scale consists of a number of words that describe different feelings and emotions. Read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you feel this way generally, that is, how you feel most of the time:

1	**2**	**3**	**4**	**5**
very slightly or not at all	a little	moderately	quite a bit	extremely

_____ interested	_____ irritable
_____ distressed	_____ alert
_____ excited	_____ ashamed
_____ upset	_____ inspired
_____ strong	_____ nervous
_____ guilty	_____ determined
_____ scared	_____ attentive
_____ hostile	_____ jittery
_____ enthusiastic	_____ active
_____ proud	_____ afraid

Scoring Instructions: Positive Affect Score: Add the scores on items 1, 3, 5, 9, 10, 12, 14, 16, 17, and 19. Scores can range from 10 – 50, with higher scores representing higher levels of positive affect. Mean Scores: Momentary 29.7 (SD 7.9); Weekly 33.3 (SD 7.2) Negative Affect Score: Add the scores on items 2, 4, 6, 7, 8, 11, 13, 15, 18, and 20. Scores can range from 10 – 50, with lower scores representing lower levels of negative affect. Mean Score: Momentary 14.8 (SD 5.4); Weekly 17.4 (SD 6.2)

Appendix 9: Demographic questionnaire

Demographics Questionnaire

Please complete this questionnaire (both sides) as honestly as possible. If there are any questions you do not feel comfortable answering, please leave them blank.

Your age: __________ years

Your sex: Male / Female

How would you describe the region of your nationality (please circle one)?

European North American Central/ South American

Asian African Australasian Other

How would you describe your ethnicity (please circle one)?

White Afro-Caribbean Indian Pakistani Bangladeshi

Chinese Japanese SouthEast Asian Other Asian

Native American Hispanic American Polynesian

Other: Please state: ________________________________

Are you attending (or have you attended) College/ University? Yes / No

If yes, what is your major? ____

Have you “played” the stock market before? Yes / No

If yes, how many years have you been playing the stock market? _______years

Appendix 10: Financial risk Profiling questionnaire

Section C

How much is your total Investment in financial markets?

less than 25k	25K - 49k	50K -74K	75K -99K	100K -124K	125K -149K	150K -174K	175K -199K	200K -249K	250K -299K	300K -399K	400K -499K	500 K -749K	750K -999K	1M-2 M	More than 2 M
◉	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

1)You are offered the following two Investment outcomes. Which do you prefer?

- ☐ £25,000 for sure
- ☐ A 50% chance of winni £50,000 or nothing otherwise

2) You are offered the following two Investments. Which do you prefer?

- ☐ £25,000 for sure
- ☐ A 65% chance of winni £50,000 or nothing otherwise.

2*) For the Question above at what probability are you willing to switch from a sure £25,000 into chance of winni £50,000 ?

50%

3) Would you take the following gamble? I will toss a coin. If it comes up heads, you win £5,000 If it comes up tails, you lose £2,500 . Would you take this gamble?

- ☐ No
- ☐ Yes, If the game was played only once?
- ☐ Yes, if the game was to be played 100 times?

3*) What is the maximum level of loss for which you would accept the gamble in q3 (game played only once)?

-£2,500

Appendix 10: Financial risk Profiling questionnaire

Section C

4) You invest £25,000 into a risky security. The investment succeeds or fails with 50/50 probability. If the investment loses, you will lose £2,500 ,If the investment wins, you gain £X. What minimum value of X would make you happy to make the investment?

£5,000

5) Which do you prefer?

- ☐ losing £25,000 for sure
- ☐ A 65% chance of losing £50,000 with 35% chance of losing nothing

5*) For the Question above at what probability of losing £50,000 are you willing to switch to sure loss of £25,000 ?

50%

6) You have inherited a share in a company worth £25,000 .Each year, the share can go up or down 10% with equal probability. After the first year, the share has gone up £2,500 . Do you now:?

a) hold the share for another year ☐ b) Sell the share ☐ c) Keep the share and buy another one. ☐

7) You have inherited a share in company worth £25,000 .Each year, the share can go up or down 10% with equal probability. After the first year, the share has gone dov £2,500 . Do you now:?

a) hold the share for another year ☐ b) Sell the share ☐ c) Keep the share and buy another one. ☐

8. Finally, please use the following free-form box to briefly explain why you invest in the financial markets. What are your aims and objectives? What is you attitude to risk?

Appendix 11: Market Risk Profiling Matlab code

Authors Mat lab code to Generate the Market Risk Profiling (The code include the Trading game &Portfolio optimisation only)

Trading game

```
function [] = TradingGame()


clc

global StockHolding CashHolding TotalWealth S YearFlag Initial Share
global SenarioResult1 SenarioResult2 SenarioResult3

InitialShare=100;
Share=InitialShare;
% StockHolding=6395;
% CashHolding=10398;
% TotalWealth=StockHolding+CashHolding;
YearFlag=2;
SenarioResult1=zeros(4,9);
SenarioResult2=zeros(4,9);
SenarioResult3=zeros(4,9);





Initial=[169.84 190.58 148.54 240.50 349.48 279.47 168.07 86.09 48.01 37.96;
    115.42 135.78 163.54 179    206.91 192.03 166.41 209.16 169.81 250.01 ;
    78.31 52.70 34.93 20.06  48.43 59.68 35.10 28.76 18.31 12.31 ];

StockHolding=Initial(1,1)*100;
CashHolding=10000*1.02;
TotalWealth=StockHolding+CashHolding;




S.fh = figure('units','pixels',...
    'position',[20 50 1330 680],...
    'menubar','none',...
    'name','TradingGame',...
    'numbertitle','off',...
    'resize','off');
S.bg(1) = uibuttongroup('units','pix',...
    'pos',[100 240 1130 420]);
%
% %% calculate
%
S.pb(1) = uicontrol('style','push',...
    'unit','pix',...
    'position',[720 120  280 40],...
    'string','Senario 1 Year 2 Performance',...
    'fontsize',12,...
    'callback',{@pb_show,S});

S.pb(2) = uicontrol('style','push',...
    'unit','pix',...
    'position',[1100 130  50 20],...
    'string','Reset',...
    'fontsize',8,...
    'callback',{@pb_reset,S});



S.pb(3) = uicontrol('style','push',...
    'unit','pix',...
    'position',[200 150  50 30],...
    'string','Buy',...
    'fontsize',10,...
```

```
    'callback',{@pb_buy,S});

S.pb(4) = uicontrol('style','push',...
    'unit','pix',...
    'position',[200 110  50 30],...
    'string','Sell',...
    'fontsize',10,...
    'callback',{@pb_sell,S});

S.pb(5) = uicontrol('style','push',...
    'unit','pix',...
    'position',[720 50  100 30],...
    'string','Report',...
    'fontsize',12,...
    'callback',{@pb_report,S});


S.bg(2) = uibuttongroup('units','pix',...
    'pos',[280 170+10 400 32]);

S.tx(1) = uicontrol('style','text',...
    'unit','pix',...
    'position',[290 175+10 100 20],...
    'string','Stock Holding',...
    'ForegroundColor', [0 0 0],...
    'fontsize',10,...
    'HorizontalAlignment','left');

S.tx(2) = uicontrol('style','text',...
    'unit','pix',...
    'position',[430 175+10 100 20],...0
    'string','Cash Holding',...
    'ForegroundColor', [0 0 0],...
    'fontsize',10,...
    'HorizontalAlignment','left');

S.tx(3) = uicontrol('style','text',...
    'unit','pix',...
    'position',[430+140 175+10 100 20],...
    'string','Total Wealth',...
    'ForegroundColor', [0 0 0],...
    'fontsize',10,...
    'HorizontalAlignment','left');

S.tx(4) = uicontrol('style','text',...
    'unit','pix',...
    'position',[190 50 150 20],...
    'string','Number of Stock Holding',...
    'ForegroundColor', [0 0 0],...
    'fontsize',10,...
    'HorizontalAlignment','left');



str1=num2str(floor(StockHolding));
S.data(1) = uicontrol('style','edit',...
    'unit','pix',...
    'position',[292 127 70 40],...
    'string',str1);

str2=num2str(floor(CashHolding));
S.data(2) = uicontrol('style','edit',...
    'unit','pix',...
    'position',[293+140 127 70 40],...
    'string',str2);

str3=num2str(floor(TotalWealth));
S.data(3) = uicontrol('style','edit',...
    'unit','pix',...
    'position',[293+140*2 127 70 40],...
    'string',str3);

str4=num2str(Share);
S.data(4) = uicontrol('style','edit',...
    'unit','pix',...
```

```
    'position',[350 50 40 20],...
    'string',str4);

YearString=['n shap\' num2str(1) '.jpg'];

matlabImage = imread(YearString);
S.ax = axes(S.bg(1),...
    'units','pixels',...
    'position',[0 10 1125 400],...
    'visible','off');
axes(S.ax)
imshow(matlabImage);
axis off
axis image


function [] = pb_show(varargin)
% Callback for pushbutton.
% S = varargin{3};  % Get the structure.

global S YearFlag Initial YearFlag Share SenarioResult1 SenarioResult2 SenarioResult3
global StockHolding CashHolding TotalWealth



I=mod(YearFlag,10);
J=(YearFlag-I)/10+1;
if YearFlag==30
    J=3;
end
if I==0
    I=10;
end

if YearFlag<=10
    SenarioResult1(1,I-1)=StockHolding;
    SenarioResult1(2,I-1)=CashHolding;
    SenarioResult1(3,I-1)=TotalWealth;
    SenarioResult1(4,I-1)=Share;
elseif YearFlag>10 && YearFlag<=20
    SenarioResult2(1,I-1)=StockHolding;
    SenarioResult2(2,I-1)=CashHolding;
    SenarioResult2(3,I-1)=TotalWealth;
    SenarioResult2(4,I-1)=Share;
elseif YearFlag>20 && YearFlag<=30
    SenarioResult3(1,I-1)=StockHolding;
    SenarioResult3(2,I-1)=CashHolding;
    SenarioResult3(3,I-1)=TotalWealth;
    SenarioResult3(4,I-1)=Share;
end

if YearFlag==30
    I;
end

StockHolding=Initial(J,I-1)*Share;
CashHolding=CashHolding*1.02;
TotalWealth=StockHolding+CashHolding;

ShowPicture;



set(S.data(1), 'String', num2str(floor(StockHolding)));
set(S.data(2), 'String', num2str(floor(CashHolding)));
set(S.data(3), 'String', num2str(floor(TotalWealth)));





function [] = pb_buy(varargin)
% Callback for pushbutton.
% S = varargin{3};  % Get the structure.

global S Initial YearFlag Share
```

```
global StockHolding CashHolding TotalWealth

I=mod(YearFlag,10);
J=(YearFlag-I)/10+1;
if I==0
    I=10;
end

Share=Share+1;

StockHolding=Initial(J,I-1)*Share;
CashHolding=TotalWealth-StockHolding;
% TotalWealth=StockHolding+CashHolding;

set(S.data(1), 'String', num2str(floor(StockHolding)));
set(S.data(2), 'String', num2str(floor(CashHolding)));
set(S.data(3), 'String', num2str(floor(TotalWealth)));
set(S.data(4), 'String', num2str(Share));

function [] = pb_sell(varargin)
% Callback for pushbutton.
% S = varargin{3};  % Get the structure.

global S Initial YearFlag Share
global StockHolding CashHolding TotalWealth

I=mod(YearFlag,10);
J=(YearFlag-I)/10+1;
if I==0
    I=10;
end

Share=Share-1;
if Share<0
    Share=0;
end

StockHolding=Initial(J,I-1)*Share;
CashHolding=TotalWealth-StockHolding;
% TotalWealth=StockHolding+CashHolding;

set(S.data(1), 'String', num2str(floor(StockHolding)));
set(S.data(2), 'String', num2str(floor(CashHolding)));
set(S.data(3), 'String', num2str(floor(TotalWealth)));
set(S.data(4), 'String', num2str(Share));

function [] = ls_Year(varargin)

global S  YearFlag
global StockHolding CashHolding TotalWealth

YearFlag=get(S.pp,'value');

function ShowPicture
global S YearFlag Initial
global StockHolding CashHolding TotalWealth

if YearFlag <= 10

    YearString=['n shap\' num2str(YearFlag) '.jpg'];
    matlabImage = imread(YearString);
    S.ax = axes(S.bg(1),...
        'units','pixels',...
        'position',[0 10 1125 400],...
        'visible','off');
    axes(S.ax)
    imshow(matlabImage);
    axis off
    axis image
    YearFlag=YearFlag+1;
    set(S.pb(1),'String',['Senario 1 Year ' num2str(YearFlag) ' Performance']);

    if YearFlag == 11
        YearString=['upward trnding\' num2str(YearFlag-10) '.jpg'];
        matlabImage = imread(YearString);
        S.ax = axes(S.bg(1),...
```

```
            'units','pixels',...
            'position',[0 10 1125 400],...
            'visible','off');
        axes(S.ax)
        imshow(matlabImage);
        axis off
        axis image
        YearFlag=12;
        set(S.pb(1),'String',['Senario 2 Year ' num2str(2) ' Performance']);

        Share=100;
        StockHolding=Initial(2,1)*Share;
        CashHolding=10000*1.02;
        TotalWealth=StockHolding+CashHolding;

        set(S.data(1), 'String', num2str(floor(StockHolding)));
        set(S.data(2), 'String', num2str(floor(CashHolding)));
        set(S.data(3), 'String', num2str(floor(TotalWealth)));
        set(S.data(4), 'String', num2str(Share));



    end

elseif YearFlag <=20
    if YearFlag == 11
        YearString=['upward trnding\' num2str(YearFlag-10) '.jpg'];
        matlabImage = imread(YearString);
        S.ax = axes(S.bg(1),...
            'units','pixels',...
            'position',[0 10 1125 400],...
            'visible','off');
        axes(S.ax)
        imshow(matlabImage);
        axis off
        axis image
        YearFlag=12;
        set(S.pb(1),'String',['Senario 2 Year ' num2str(2) ' Performance']);

    else
        YearString=['upward trnding\' num2str(YearFlag-10) '.jpg'];
        matlabImage = imread(YearString);
        S.ax = axes(S.bg(1),...
            'units','pixels',...
            'position',[0 10 1125 400],...
            'visible','off');
        axes(S.ax)
        imshow(matlabImage);
        axis off
        axis image
        YearFlag=YearFlag+1;
        temp=mod(YearFlag,10);
        if temp==0
            temp=10;
        end
        set(S.pb(1),'String',['Senario 2 Year ' num2str(temp) ' Performance']);
    end

    if YearFlag == 21
        YearString=['down trending\' num2str(YearFlag-20) '.jpg'];
        matlabImage = imread(YearString);
        S.ax = axes(S.bg(1),...
            'units','pixels',...
            'position',[0 10 1125 400],...
            'visible','off');
        axes(S.ax)
        imshow(matlabImage);
        axis off
        axis image
        YearFlag=22;
        set(S.pb(1),'String',['Senario 3 Year ' num2str(2) ' Performance']);

                Share=100;
        StockHolding=Initial(3,1)*Share;
        CashHolding=10000*1.02;
```

```
        TotalWealth=StockHolding+CashHolding;

        set(S.data(1), 'String', num2str(floor(StockHolding)));
        set(S.data(2), 'String', num2str(floor(CashHolding)));
        set(S.data(3), 'String', num2str(floor(TotalWealth)));
        set(S.data(4), 'String', num2str(Share));



    end

elseif YearFlag <=30

    if YearFlag == 21
        YearString=['down trending\' num2str(YearFlag-20) '.jpg'];
        matlabImage = imread(YearString);
        S.ax = axes(S.bg(1),...
            'units','pixels',...
            'position',[0 10 1125 400],...
            'visible','off');
        axes(S.ax)
        imshow(matlabImage);
        axis off
        axis image
        YearFlag=22;
        set(S.pb(1),'String',['Senario 3 Year ' num2str(2) ' Performance']);
    else
        YearString=['down trending\' num2str(YearFlag-20) '.jpg'];
        matlabImage = imread(YearString);
        S.ax = axes(S.bg(1),...
            'units','pixels',...
            'position',[0 10 1125 400],...
            'visible','off');
        axes(S.ax)
        imshow(matlabImage);
        axis off
        axis image
        YearFlag=YearFlag+1;
        temp=mod(YearFlag,10);
        if temp==0
            temp=10;
        end
        set(S.pb(1),'String',['Senario 3 Year ' num2str(temp) ' Performance']);
    end
end

if YearFlag>30
    YearFlag=30;
end

function [] = pb_report(varargin)


global SenarioResult1 SenarioResult2 SenarioResult3 YearFlag

if YearFlag==30

import mlreportgen.dom.*;
doc = Document('groupReport','html');
disclaimerHead = Heading(2,'Results');
% disclaimerIntro = Paragraph('The following results assume:');
% disclaimerList = UnorderedList(...
%     {'Temperature between 30 and 70 degrees F',...
%     'Wind less than 20 MPH','Dry road conditions'});
disclaimer = Group();
append(disclaimer,disclaimerHead);
% append(disclaimer,disclaimerIntro);
% append(disclaimer,disclaimerList);
append(doc,disclaimer);

p1 = Paragraph('Senario 1:, ');
p1.Bold = true;
append(doc,p1);

h=figure(2);
set(h,'visible','off');
```

```
hold on
plot(1:9,SenarioResult1(1,:)/1000,1:9,SenarioResult1(2,:)/1000,1:9,SenarioResult1(3,:)/1000);
title('Graph of Stock Holding, Cash Holding and Total Wealth')
axis([0 10 0 max(SenarioResult1(3,:)/1000)*1.3])
xlabel('Year') % x-axis label
ylabel('Value / k£') % y-axis label
legend('Graph of Stock Holding', 'Cash Holding' , 'Total Wealth')
saveas(2,'SR1.jpg');
close(2)
hold off
imageObj1 = Image('SR1.jpg');
append(doc,imageObj1);

h=figure(3);
set(h,'visible','off');
hold on
plot(1:9,SenarioResult2(4,:));
title('Number of Shares')
axis([0 10 max(SenarioResult2(4,:))*0.5 max(SenarioResult2(4,:))*1.3])
xlabel('Year') % x-axis label
ylabel('Number of Shares') % y-axis label
% legend('Graph of Stock Holding', 'Cash Holding' , 'Total Wealth')
saveas(3,'Share1.jpg');
close(3)
hold off
imageObj2 = Image('Share1.jpg');
append(doc,imageObj2);



%% Senario 2

p2 = Paragraph('Senario 2:, ');
p2.Bold = true;
append(doc,p2);

h=figure(4);
set(h,'visible','off');
hold on
plot(1:9,SenarioResult3(1,:)/1000,1:9,SenarioResult3(2,:)/1000,1:9,SenarioResult3(3,:)/1000);
title('Graph of Stock Holding, Cash Holding and Total Wealth')
axis([0 10 0 max(SenarioResult3(3,:)/1000)*1.3])
xlabel('Year') % x-axis label
ylabel('Value / k£') % y-axis label
legend('Graph of Stock Holding', 'Cash Holding' , 'Total Wealth')
saveas(4,'SR3.jpg');
close(4)
hold off
imageObj3 = Image('SR3.jpg');
append(doc,imageObj3);

h=figure(7);
set(h,'visible','off');
hold on
plot(1:9,SenarioResult2(4,:));
title('Number of Shares')
axis([0 10 max(SenarioResult2(4,:))*0.5 max(SenarioResult2(4,:))*1.3])
xlabel('Year') % x-axis label
ylabel('Number of Shares') % y-axis label
% legend('Graph of Stock Holding', 'Cash Holding' , 'Total Wealth')
saveas(7,'Share2.jpg');
close(7)
hold off
imageObj4 = Image('Share2.jpg');
append(doc,imageObj4);


%%Senario 3
p3 = Paragraph('Senario 3:, ');
p3.Bold = true;
append(doc,p3);

h=figure(5);
set(h,'visible','off');
hold on
plot(1:9,SenarioResult3(1,:)/1000,1:9,SenarioResult3(2,:)/1000,1:9,SenarioResult3(3,:)/1000);
```

```
title('Graph of Stock Holding, Cash Holding and Total Wealth')
axis([0 10 0 max(SenarioResult3(3,:)/1000)*1.3])
xlabel('Year') % x-axis label
ylabel('Value / k£') % y-axis label
legend('Graph of Stock Holding', 'Cash Holding' , 'Total Wealth')
saveas(5,'SR2.jpg');
close(5)
hold off
imageObj5 = Image('SR3.jpg');
append(doc,imageObj5);

h=figure(6);
set(h,'visible','off');
hold on
plot(1:9,SenarioResult3(4,:));
title('Number of Shares')
axis([0 10 max(SenarioResult3(4,:))*0.5 max(SenarioResult3(4,:))*1.3])
xlabel('Year') % x-axis label
ylabel('Number of Shares') % y-axis label
% legend('Graph of Stock Holding', 'Cash Holding' , 'Total Wealth')
saveas(6,'Share3.jpg');
close(6)
hold off
imageObj6 = Image('Share3.jpg');
append(doc,imageObj6);

append(doc,disclaimer);


close(doc);
rptview('groupReport','html');


else
    i=1
end


classdef Portfolio < handle
```

Portfolio Optimization

```
    properties (Access = protected)
        % Imported data
        prices         = [];      % Prices series
        benchmark      = [];      % Benchmark series
        dates          = [];      % Dates series
        priceslabels   = [];      % Prices series labels
        benchmarklabel = [];      % Benchmark label
        % Asset selection
        assetselection = [];      % Asset selection vector (logical)
        % Return series
        decayfactor    = 1;       % Decay factor for weighted returns
        uselogrets     = false;   % True for continuously compounded returns
        % Optimization results
        pf_rsk         = [];      % Portfolio risks
        pf_ret         = [];      % Portfolio returns
        pf_weights     = [];      % Portfolio weights
        % Business days assumtion
        businessdayspermonth = 21;
        businessdaysperyear  = 21*12;  % 252 days
    end


    methods (Access = public)

        function this = Portfolio()
        % Constructor
        end

        % Getter methods
function prices = getPrices(this),

prices =this.prices(:,this.assetselection);                 end
```

```
function benchmark = getBenchmark(this),           benchmark = this.benchmark;
end
        function dates = getDates(this),                   dates = this.dates;
end
        function priceslabels = getPricesLabels(this),     priceslabels =
this.priceslabels(this.assetselection);       end
        function benchmarklabel = getBenchmarkLabel(this), benchmarklabel =
this.benchmarklabel;                        end
        function assetselection = getAssetSelection(this), assetselection =
this.assetselection;                        end

        function returns = getReturnSeries(this)
        % Compute return series

            % Returns are depending on decay factor and compounding option
            % Call helper function
            returns = this.computeReturnSeries(this.prices(:,this.assetselection));
        end

        function [exp_ret,exp_rsk,exp_covariance,annualized_ret,annualized_rsk] =
getStatistics(this,all_assets)
        % Compute daily expected risk/return and covariance, and annualized risk/return of
selected assets
        % - if input "all_assets" is defined and true, return stats of complete data set

            % compute unweighted return series
            if exist('all_assets','var') && all_assets == true
                returns = this.computeReturnSeries(this.prices,1);
            else
                returns = this.computeReturnSeries(this.prices(:,this.assetselection),1);
            end
            % get stats using ewstats
            [exp_ret,exp_covariance] = ewstats(returns,this.decayfactor);
            exp_rsk = sqrt(diag(exp_covariance));
            exp_rsk = exp_rsk(:)';  % row vector
            % annualized return and volatility
            annualized_rsk = exp_rsk./sqrt(1/this.businessdaysperyear);
            annualized_ret = exp_ret*this.businessdaysperyear;
        end

        function [exp_ret,exp_rsk,annualized_ret,annualized_rsk] =
getBenchmarkStatistics(this)
        % Compute daily expected return/risk of benchmark series

            if isempty(this.benchmark)
                exp_ret = [];
                exp_rsk = [];
                annualized_rsk = [];
                annualized_ret = [];
                return
            end
            % compute unweighted benchmark return series
            benchmarkreturns = this.computeReturnSeries(this.benchmark,1);
            % compute stats using ewstats
            [exp_ret,exp_variance] = ewstats(benchmarkreturns,this.decayfactor);
            exp_rsk = sqrt(exp_variance);
            % annualized return and volatility
            annualized_rsk = exp_rsk./sqrt(1/this.businessdaysperyear);
            annualized_ret = exp_ret*this.businessdaysperyear;
        end

        function enableAsset(this,assetnumber,state)
        % Enable/disable single asset for optimzation
            if (assetnumber > 0) && (assetnumber <= length(this.assetselection)) &&
islogical(state)
                this.assetselection(assetnumber) = state;
            end
        end

        function useLogReturns(this,val)
        % Select logarithmic/simple return series
           this.uselogrets = val;
        end

        function setDecayFactor(this,val)
        % Set new decay factor
            this.decayfactor = val;
```

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